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# Biomechanical Models for Human-Computer Interaction

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*Дякую батькам*

*For my parents*



# Abstract

Post-desktop user interfaces, such as smartphones, tablets, interactive tabletops, public displays and mid-air interfaces, already are a ubiquitous part of everyday human life, or have the potential to be. One of the key features of these interfaces is the reduced number or even absence of input movement constraints imposed by a device form-factor. This freedom is advantageous for users, allowing them to interact with computers using more natural limb movements; however, it is a source of 4 issues for research and design of post-desktop interfaces which make traditional analysis methods inefficient: the new movement space is orders of magnitude larger than the one analyzed for traditional desktops; the existing knowledge on post-desktop input methods is sparse and sporadic; the movement space is non-uniform with respect to performance; and traditional methods are ineffective or inefficient in tackling physical ergonomics pitfalls in post-desktop interfaces. These issues lead to the research problem of efficient assessment, analysis and design methods for high-throughput ergonomic post-desktop interfaces.

To solve this research problem and support researchers and designers, this thesis proposes efficient experiment- and model-based assessment methods for post-desktop user interfaces. We achieve this through the following contributions:

- adopt optical motion capture and biomechanical simulation for HCI experiments as a versatile source of both performance and ergonomics data describing an input method;
- identify applicability limits of the method for a range of HCI tasks;
- validate the method outputs against ground truth recordings in typical HCI setting;
- demonstrate the added value of the method in analysis of performance and ergonomics of touchscreen devices; and
- summarize performance and ergonomics of a movement space through a clustering of physiological data.

The proposed method successfully deals with the 4 above-mentioned issues of post-desktop input. The efficiency of the methods makes it possible to effectively tackle the issue of large post-desktop movement spaces both at early design stages (through a generic model of a movement space) as well as at later design stages (through user studies). The method provides rich data on physical ergonomics (joint angles and moments, muscle forces and activations, energy expenditure and fatigue), making it possible to solve the issue of ergonomics pitfalls. Additionally, the method provides performance data (speed, accuracy and throughput) which can be related to the physiological data to solve the issue of non-uniformity of movement space. In our adaptation the method does not require experimenters to have specialized expertise, thus making it accessible to a wide range of researchers and designers and contributing towards the solution of the issue of post-desktop knowledge sparsity.

# Zusammenfassung

Post-Desktop Benutzerschnittstellen, wie zum Beispiel Smartphones, Tablets, interaktive Tische, Public Displays und berührungslose Schnittstellen, sind bereits ein Teil des täglichen menschlichen Lebens oder haben Potenzial, dies zu werden. Eines der wichtigsten Merkmale dieser Schnittstellen ist die reduzierte Zahl oder sogar Abwesenheit von räumlichen Beschränkungen der Eingabebewegungen, welche durch das Gerät vorgegeben werden. Diese Freiheit ist von Vorteil für die Benutzer und erlaubt ihnen eine Interaktion mit Rechnern mittels natürlicher Bewegungen, z.B. der Extremitäten. Gleichzeitig erzeugt sie Schwierigkeiten für Forschung und Design von Post-Desktop Benutzeroberflächen: der neue Bewegungsraum ist um Größenordnungen größer als der früher analysierte Bewegungsraum des Desktops; das vorhandene Wissen über Post-Desktop Eingabemethoden ist spärlich und sporadisch; der Bewegungsraum ist ungleichmäßig in Bezug auf Kenngrößen der Benutzerleistung, wie etwa Bewegungszeiten; traditionelle Methoden sind ineffektiv und ineffizient bei der Lösung von Problemen der physischen Ergonomie von Post-Desktop Benutzerschnittstellen. Diese Schwierigkeiten führen zur Forschungsproblem bezüglich der effizienten Auswertung-, Analyse- und Entwurfsmethoden für ergonomische hochleistungs Post-Desktop Benutzerschnittstellen.

Zur Lösung dieser Probleme und zur Unterstützung von des Designs solcher Schnittstellen schlägt diese Arbeit effiziente Experimentalmethoden und modellbasierte Auswertungsmethoden für Post-Desktop Benutzerschnittstellen. Wir erreichen dieses Ziel durch die folgenden Beiträge:

- wir passen optische Bewegungserfassung und biomechanische Simulation an MCI-Experimente an, um vielseitige Benutzerleistungsdaten und ergonomische Daten von Eingabemethoden effizient zu sammeln;
- wir ermitteln die Grenzen des Anwendungsbereiches der Methode für diverse MCI Aufgaben;

- wir validieren die Ergebnisse dieser Methode im Vergleich zu etablierten Methoden der MCI;
- wir zeigen den Mehrwert der Methode zur Ermittlung der Benutzerleistung und Ergonomie von Touch-Screen Geräten auf; und
- wir fassen die Benutzerleistung und Ergonomie des Bewegungsraumes mittels Clusteranalyse von physiologischen Daten zusammen.

Die vorgeschlagene Methode begegnet mit Erfolg den vier oben genannten Schwierigkeiten von Post-Desktop Benutzerschnittstellen. Die Effizienz der Methode erlaubt effektive Lösung der Schwierigkeit der Größe des Bewegungsraumes von Post-Desktop Benutzerschnittstellen in frühen Entwicklungsphasen (durch clusterbasierte Modelle des Bewegungsraum) und in späteren Entwicklungsphasen (durch Benutzerexperimente). Die Methode generiert vielseitige ergonomische Daten (Gelenkwinkel und -momente, Muskelkräfte und -aktivierungen, Energieaufwand und Ermüdung) und erlaubt damit die Messung und Verbesserung der physischen Ergonomie. Zusätzlich generiert die Methode Daten der Benutzerleistung (Geschwindigkeit, Genauigkeit und Bandbreite), welche mit den physiologischen Daten verglichen werden können, um die Schwierigkeit der Ungleichmäßigkeit des Bewegungsraumes zu lösen. Unsere Anpassung der Methode erfordert keine Spezialkenntnisse von Experimentatoren, und ist so für ein breites Spektrum von Forschern und Designern anwendbar. Damit trägt sie zur Lösung der Schwierigkeit von Post-Desktop Benutzerschnittstellen bei.



# Contents

<b>Acknowledgements</b>	<b>iii</b>
<b>Abstract</b>	<b>vii</b>
<b>Zusammenfassung</b>	<b>ix</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Benefits and Challenges of Post-Desktop Input Methods . . .	2
1.2 Main Objectives . . . . .	7
1.3 Approach and Methods . . . . .	7
1.4 Problem Statement and Research Questions . . . . .	10
1.5 Contributions . . . . .	13
1.6 Relevant Publications . . . . .	15
1.7 Thesis Structure . . . . .	17
<b>2 Background &amp; Related Work</b>	<b>19</b>
2.1 Input Method Design . . . . .	20
2.1.1 Design Process . . . . .	21
2.1.2 Performance & Ergonomics—Key Objectives of In- put Method Design . . . . .	24
2.2 Body of Knowledge in Desktop and Post-Desktop Interface Design . . . . .	24
2.2.1 Traditional Input Methods . . . . .	25
2.2.2 Touch-Based Input Methods . . . . .	29
2.2.3 Mid-Air Input Methods . . . . .	32
2.2.4 Discussion . . . . .	34
2.3 Physical Ergonomics . . . . .	35
2.3.1 Physical Ergonomics Data Collection Methods . . . .	35
2.3.2 Ergonomical Models . . . . .	44
2.3.3 Digital Human Simulation in Ergonomics and HCI .	47

## Contents

---

2.3.4	Discussion . . . . .	48
2.4	Input Performance Assessment Methods . . . . .	49
2.4.1	Discussion . . . . .	50
2.5	Motion Capture-Based Biomechanical Simulation . . . . .	51
2.5.1	Optical Motion Capture . . . . .	52
2.5.2	Musculoskeletal Models . . . . .	54
2.5.3	Biomechanical Simulation . . . . .	60
2.5.4	Improvement over Traditional HCI Methods . . . . .	64
2.5.5	Previous Validations of Biomechanical Models and Simulation . . . . .	66
2.5.6	Discussion . . . . .	67
2.6	Summarization and Clustering of Physiological Data . . . . .	67
2.6.1	Discussion . . . . .	69
2.7	Summary . . . . .	69
<b>3</b>	<b>The HCI Biomechanics Pipeline</b>	<b>71</b>
3.1	Introduction . . . . .	71
3.2	General Adaptation of the Method for HCI Studies . . . . .	73
3.3	Adaptation of Experimental Design . . . . .	74
3.4	Data Preprocessing . . . . .	77
3.5	Extraction of Performance Data . . . . .	78
3.6	Extraction of Physical Ergonomics Data . . . . .	79
3.7	Spatial Registrations of Data . . . . .	79
3.8	Data Representation on Multiple Aggregation Levels . . . . .	80
3.9	Interactive Analysis . . . . .	80
3.10	Summary . . . . .	82
<b>4</b>	<b>Applicability of the Simulation for HCI Tasks</b>	<b>83</b>
4.1	Introduction . . . . .	83
4.2	General Setup . . . . .	84
4.3	User Study . . . . .	84
4.4	Analyses . . . . .	86
4.5	Results . . . . .	86
4.6	Discussion . . . . .	88
<b>5</b>	<b>Validity of the Simulation in the HCI Setting</b>	<b>91</b>
5.1	Introduction . . . . .	91
5.2	Sources of Error in Biomechanical Simulation . . . . .	93
5.3	User Study . . . . .	96

---

5.4	Preprocessing and Analyses . . . . .	97
5.5	Results . . . . .	98
5.6	Discussion . . . . .	99
<b>6</b>	<b>Knowledge Added by Biomechanical Simulation in Input Method Design</b>	<b>103</b>
6.1	Performance and Ergonomics of Touch Surfaces . . . . .	103
6.1.1	Introduction . . . . .	103
6.1.2	Experimental Method . . . . .	106
6.1.3	Analyses . . . . .	109
6.1.4	The TOUCHCORPUS dataset . . . . .	110
6.1.5	Results . . . . .	111
6.1.6	Discussion . . . . .	119
6.2	Physical Ergonomics of Tablet Interaction . . . . .	122
6.2.1	Introduction . . . . .	122
6.2.2	Methods . . . . .	122
6.2.3	Results & Discussion . . . . .	123
6.3	Summary . . . . .	125
<b>7</b>	<b>Lowering Barriers for Non-Experts: Overview of the Full-Arm Movement Space through Muscle Co-Activation Clustering</b>	<b>127</b>
7.1	Introduction . . . . .	127
7.2	Data Collection . . . . .	130
7.2.1	User Study . . . . .	130
7.2.2	Validation . . . . .	132
7.3	Overview of the Dataset . . . . .	133
7.4	Clustering . . . . .	136
7.4.1	Method . . . . .	136
7.4.2	Overview of Clustering . . . . .	139
7.4.3	Description of Clusters . . . . .	146
7.4.4	Performance Analysis per Cluster . . . . .	149
7.5	Input Method Design . . . . .	151
7.5.1	Application Algorithm . . . . .	151
7.5.2	Case 1: Mid-Air Keyboard Placement . . . . .	151
7.5.3	Case 2: Public Display . . . . .	153
7.5.4	Case 3: Smartwatch input . . . . .	153
7.6	Discussion . . . . .	155

## Contents

---

<b>8</b>	<b>Conclusions</b>	<b>159</b>
8.1	Discussion . . . . .	159
8.2	Future Research Directions . . . . .	167
8.2.1	Expanding Applicability Limits . . . . .	167
8.2.2	Streamlining the method . . . . .	168
8.2.3	Improving biomechanical simulation software . . . . .	168
8.2.4	Improving Validity of the Simulation . . . . .	169
8.2.5	Developing a Predictive Model and Input Method Optimization . . . . .	169
8.3	Concluding Remarks . . . . .	170
	<b>List of Figures</b>	<b>171</b>
	<b>List of Tables</b>	<b>173</b>
	<b>Bibliography</b>	<b>175</b>

# Chapter 1

## Introduction

For decades humans have been interacting with computers using a narrow range of input devices such as keyboards, mice or touchpads. But recent developments in touch and motion tracking technology have allowed a new generation of input methods to emerge. Post-desktop user interfaces, such as smartphones, tablets, interactive tabletops, public displays, gesture-based and full-body interfaces, e.g. Leap Motion or Microsoft Kinect, already are or have the potential to become ubiquitous everyday user interfaces, in particular considering trends in the penetration of computing devices into all spheres of human life. One of the key features of these input methods is the reduced number or even absence of interaction movement constraints imposed by a device form-factor. This freedom is advantageous for users, as it allows more natural interaction with computers. However, development of post-desktop user interfaces is a challenging task for interaction designers and researchers, as traditional analysis and evaluation methods become inefficient in the new setting.

This introductory chapter provides an overview of current trends in computer input methods and Human-Computer Interaction (HCI), corresponding design problems, traditional solving approaches and their deficiencies in the new context. We motivate our search for new alternative methods and tools which can fill the emerging gaps in knowledge and inform the design process. We propose motion capture-based biomechanical simulation as a potential method to deal with the issues of the post-desktop interface design. We formulate the research problem and identify the main challenges in adoption of the new method in HCI. Further, we list our specific contributions in the adoption and adaptation of biomechanical simulation for HCI tasks and corresponding scientific publications. Finally, we briefly describe the outline and structure of this thesis.

## 1.1 Benefits and Challenges of Post-Desktop Input Methods

There are many ways humans can express their *intent* to the external world, for example voice, voluntary movements, biochemical activity, electrical peripheral neural signals or brain activity. However, for computer input, the only appropriate information medium in most cases is human *voluntary movement*. It can be expressed as a button press, a mouse-mediated aimed movement, a direct touch aimed movement, a touchscreen or mid-air gesture, full-body movement, etc.

For decades, Human-Computer Interaction (HCI) was focused on a narrow range of devices for computer input operated mostly by small discreet hand and finger movements, for example keyboard, mouse or touchpad. But rapid developments of touch and motion sensing technology in recent years give us more freedom to broaden the interaction space and use not only our fingertips, but the *whole body* for computer input. Nowadays touchscreen, tabletop, Inertial Measurement Unit (IMU), camera or depth sensor-based interfaces have become a ubiquitous part of human life.

The input methods beyond the desktop are capable to provide more intuitive, easy-to-learn and enjoyable interaction, called *Natural User Interfaces (NUI)* [1]. Each input method or gesture can be selected so that it matches users' internal knowledge and understanding of an action to be performed. For example, NUI allows manipulation of virtual 2D and 3D objects resulting in object transformations equivalent to the ones known from the physical-world manipulations. While computing devices penetrate into all spheres of human life as the internet of things [2], these input methods gain huge potential to be applied everywhere, without explicit visible physical input artifacts, and improve the quality of human lives.

It is considered that the naturalness of interaction with post-desktop interfaces provides improved *User Experience (UX)* and as a result they are particularly desirable for entertainment, and for most new systems in general [3]. User Experience is a "user's perceptions and responses that result from the use or anticipated use of a product, system or service" [4]. It depends on a user's internal state, the properties of the product and the context of the interaction. To large extent UX is a subjective measure, but objective measures of *performance* and *physical ergonomics* reflect on users' perceptions: proper measures lead to satisfactory or improved

UX, while bad ones degrade UX significantly, in particular in long-term use [5]. Thus it can be considered that proper physical ergonomics and performance are prerequisites for positive UX.

The post-desktop input methods give users freedom to use their advantages in multiple application scenarios, but also pose big challenges to interface designers and HCI researchers due to the massive design space of possible movements, non-uniformity with respect to performance, absence of a solid background in the area and multiple physical ergonomics pitfalls.

**The first issue concerns the size of design and interaction space:** all traditional input methods are linked to a physical input artifact, which limits the design space and defines the potential movement space. For example, the keyboard limits its design space to a sequence of discrete keypress events, its hand movement space covers a small parallelogram volume over the keys, and fingers perform flexion-extension movements when pressing a key. The mouse limits its design space to planar aimed movements, a few button presses and scroll wheel operations, and the movement space covers usually smaller than  $30\text{cm} \times 30\text{cm}$ , mostly planar movements for the hand with up to 5cm in height during clutching, and a few button and scroll wheel-specific flexion-extension movements for the fingers. In contrast to these, the post-desktop input methods allow complete freedom in continuous gesture, trajectory and manipulation-based interaction, expanding the design space immensely. Even the design space of a keyboard is quite large, although it is based on discrete key presses: the total number of possible letter to event mappings (for example keyboard layouts) is  $26! \approx 4 \times 10^{26}$ , leaving aside different types of possible event sets. However, for post-desktop interfaces the design space is continuous and the number of possible events, for example trajectory-based gestures, which can be mapped to computer actions grows to infinity. For example, considering such elementary action as a short directed movement and the directional resolution of  $10^\circ$  we get a set of 614 alternatives; further, if we use this set in trajectory-based gestures consisting of a sequence of 12 such elementary actions (e.g. three characters "M"), the design space already becomes  $614^{12} \approx 3 \times 10^{33}$ , leaving smooth continuous movements aside. The movement space includes all possible postures and movements of human fingers, hands, arms and the whole body, and is constrained only by the body's internal skeletal joint constraints. Even considering a single arm end-effector only, the corresponding movement volume is 200 times larger than that of the mouse. Such large design and

movement spaces complicate analysis of post-desktop input methods and make traditional approaches inefficient or ineffective.

**The second issue concerns the absence of solid body of knowledge in design of post-desktop input methods.** A *body of knowledge* is “a systematic collection of activities and outcomes in terms of their values, constructs, models, principles and instantiations, which arises from continuous discovery and validation work by members of the profession and enables self-reflective growth and reproduction of the profession” [6]. Years of research and practice on many aspects of traditional input methods have created a solid body of knowledge allowing effective development of user interfaces based on these input methods. However, the existing knowledge, namely design principles, models, templates and processes, cannot be easily transferred to post-desktop input methods, as they provide broader input and movement spaces than the ones studied in the past. Even the ubiquitous in HCI and extensively validated Fitts’ law is limited in applications to post-desktop input methods, as described in the following paragraph. Another example: application of the traditional desktop display layout with a menu placement at the top of the screen to a large interactive public display leads to poor performance and ergonomics, as the menu located above users’ heads requires significant effort to operate, and even becomes an accessibility problem for smaller or shorter users. Instead of extrapolating existing knowledge of traditional interfaces, the post-desktop input methods require individual broader data collection and analysis, which would eventually lead to development of rules, best practices and templates for effective and efficient post-desktop interface design. Unfortunately, the complexity of traditional analysis methods in application to post-desktop interfaces leads only to sparse knowledge in the area, sporadically gathered in user studies.

**The third issue concerns non-uniformity of the movement space with respect to performance.** Generally *user performance* is a measure describing efficiency and quality in task completion, or more specifically users’ speed and number of errors [7]. In the case of goal-directed movements, in HCI a common performance measure is speed and accuracy, or their relationship described by Fitts’ law and combined into a single measure of throughput [8]. The traditional HCI input performance description and modeling methods (Fitts’ law and its derivatives) do not consider the effect of the spatial location of targets with respect to humans on the movement accuracy, speed and throughput and assume that



the whole movement space is uniform. While this assumption is reasonable for small movement spaces of traditional input methods, it does not work for post-desktop input methods, as the movements in various regions of the large movement space are executed by different kinematic chains and neuromuscular networks providing different levels of performance and leading to *non-uniformity*. Thus, new performance models need to be developed and applied for the analysis of post-desktop input methods, which would take into account the non-uniformity and represent all nuances of human movements.

**The fourth issue concerns a wide range of potential physical ergonomics problems induced by post-desktop input methods.** *Physical ergonomics* describes the risks to human musculoskeletal system imposed by regular physical work activity or a particular movement task [9]. In the context of HCI, physical ergonomics can be interpreted as a biomechanical cost of interaction consisting from two components: musculoskeletal health risks and general energy expenditure coupled with fatigue. It has been known for decades that prolonged or repetitive postures, movements and human body-internal stresses can lead to injuries and musculoskeletal disorders, in general known as cumulative trauma or repetitive strain injuries (RSI). For example, although the loads caused by a mouse and keyboard on our musculoskeletal system are relatively low, after prolonged repetitive use over years, they often lead to carpal tunnel syndrome or tendinitis. To reduce the bad impacts on human health, these devices were extensively studied for physical ergonomics issues, resulting in an elaborate set of related ergonomic recommendations. Nowadays most device manufacturers take physical ergonomics recommendations into account (specific shape, button pressing damping forces, size, weight of devices), some of them putting physical ergonomics in first place (vertical or tilted mouse, split keyboard, vertical keyboard). Besides being a source of RSI, the input methods with poor physical ergonomics often completely fail to be adopted by a wide population of users even when they have excellent performance and learnability properties. An example of this effect is the light pen, which was initially considered to be the mouse-killer due to its intuitiveness, directness and high performance [10], but failed to be widely adopted by computer users because of the induced load and resulting fatigue to the shoulder and arm muscles. The post-desktop input methods involve new types of postures and movements, whose physical ergonomics effects have to be properly studied and understood before industrial production and wide public adop-

tion. Unless the post-desktop interfaces will be developed according to ergonomics recommendations derived from physical ergonomics studies, they will either fail to be adopted, or will lead to a variety of disorders.

Unfortunately, even nowadays, only a few years after the beginning of the post-desktop era in industry, we can already observe examples of major failures, such as a number of Microsoft Kinect applications [11] or Leap Motion [12], as well as adverse effects of poor designs on human health, e.g. “smartphone neck” [13], “Blackberry thumb” [14] or “Gorilla arm” [15]. The four issues mentioned in the previous paragraphs make it extremely demanding for companies to perform extensive analysis of their designs before reaching the users. Additionally, the time-to-market period, continuously shrinking under pressure from competitors, does not allow thorough assessment of performance and ergonomics using traditional methods, barely leaving time for technical testing of a product. As a result many interactive products either provide poor ergonomics (mid-air or touchscreen interfaces), or completely shift ergonomics decisions to the end-user without giving any warning or recommendation (hand-held devices). To solve this problem, we need more efficient performance and ergonomics analysis methods for post-desktop interfaces, which can fit tight timelines in industry and research.

The traditional approach to design of input methods was based on *User-Centered Design (UCD)* [16]. UCD is an iterative process alternating phases of context analysis, design, prototyping and evaluation of a user interface prototype. While it can effectively lead to good designs, every iteration becomes extremely time consuming, in particular in design stages which involve user studies with a large design space and a variety of design alternatives. To avoid this cost, some user evaluations can be replaced by *predictive models or simulations* characterizing users. However, there is a lack of such models for post-desktop input methods describing physical ergonomics and performance.

Existing methods which were traditionally applied for physical ergonomics assessment reach their limits when working with post-desktop interfaces due to their application cost, complexity, inaccuracy or superficiality. For example, questionnaires are subjective and unreliable, and often people cannot perceive the musculoskeletal discomfort or strain in short-term studies, while long-term usage can lead to RSI. From the side of objective measures, surface electromyography (sEMG) provides activation signals only for the close-to-skin muscles, and it suffers from cross-talk and low reliability in dynamic movements. Invasive electromyogra-

phy (iEMG) is too complex to apply and necessitates a clinical setting. Additionally, most objective measurement methods are too cumbersome to apply on the whole body and could interfere with the naturalness of the interaction.

In order to make successful post-desktop interfaces, *new, more efficient and versatile physical ergonomics and performance methods need to be proposed*, explored and developed for HCI experiments, and ideally, further adopted by the industry.

## 1.2 Main Objectives

As described above, post-desktop input methods need to assess both performance and ergonomics within HCI. Traditional physical ergonomics methods are too complex, costly, time-consuming, invasive to the human body or intrusive to natural interaction. This prohibits an efficient analysis, assessment and design process of post-desktop input methods.

**This thesis aims to advance the current theoretical and methodological base of HCI, as well as provide practitioners with more efficient methods for performance and ergonomics evaluation of post-desktop interfaces.** This is achieved through the following objectives:

- provide an efficient performance and ergonomics assessment method applicable and valid for analysis of post-desktop interfaces and tackling the 4 issues described in the previous section;
- demonstrate the knowledge added by the method to the HCI field by solving real HCI problems;
- inform the design of post-desktop interfaces with the proposed method as a source of knowledge.

## 1.3 Approach and Methods

To achieve the research objectives, as a first step we need to propose a method suitable for HCI deployment and efficiently dealing with post-desktop interface research issues. We identify the potential method through review of current and previous work from relevant research fields: ergonomics, biomechanics, kinesiology, sports and rehabilitation. As the most suitable method, we consider motion capture-based biomechanical simulation.

**Motion capture-based biomechanical simulation** is a method which integrates optical motion capture to record the human body and limb movements with simulation of biomechanical processes producing them. As the first step, *optical motion capture* records 3D trajectories of markers attached to all segments of the human body according to anatomical landmarks. These marker trajectories completely describe kinematics of the human body, and directly are a source of movement performance information. As the next step, *biomechanical simulation* transforms marker trajectories in 3D space into human body skeletal kinematics, dynamics and muscular control [17], which are a rich data source for ergonomics analysis. This method is currently applied in research on rehabilitation [18] and sports [19] and its potential has been recognized for industrial ergonomics research [20]. It has potential to become a great tool also for HCI research and interface design, since the motion capture equipment and computational cost are not a bottleneck anymore [21], and a range of biomechanical models and simulation software are available for a reasonable price (SIMM, AnyBody, LifeModeler), or even open source (OpenSim). However, before the work described in this thesis, motion capture-based biomechanical simulation has not been applied in HCI.

The method can tackle the four issues of post-desktop input by providing data for efficient and cheap analysis of both performance and ergonomics, namely *biomechanical stresses, muscular loads and end-effector speed and accuracy*. As it does not restrict natural human movements by sparsely attached markers, it can be applied to most types of movement-based HCI tasks. However, for analysis of post-desktop interfaces, this method brings the largest benefits providing information to avoid cumbersome postures or straining movements. As the method is efficient to apply, it is possible to use it not only for evaluation of interface prototypes, but for recording of data describing the whole movement space, which can be used to inform the design. Additionally, performance and ergonomics data can be analyzed synchronously in a combined manner to identify optimal trade-offs between them, or to relate performance data with respect to biomechanical system segments executing the movement.

In contrast to existing design methods such as UCD, and previous physical ergonomics methods such as EMG or videometry, the application cost, required expertise, intrusiveness to the task and invasiveness to the human body of motion capture-based biomechanical simulation are at an acceptable level. However, before wide adoption of the method in HCI, a few problems still need to be solved. In contrast to the fields where

the method is already successfully deployed (eg. rehabilitation, sports), the HCI field has few key specifics:

- it covers a wide range of movement types, from barely observable finger movements to large whole-body movements;
- HCI experimenters do not have much experience with biomechanics or physiology;
- there are fewer resources which can be spent on each study participant, prohibiting fine-tuning of experiment and model for each participant;
- there is no advance interest in a particular body segment; rather, the segment of interest is identified in the study;
- the focus is on analysis of the whole population rather than a particular participant.

We need to identify applicability limits of the method for HCI-specific movements, validate the method outputs in the HCI setting, evaluate usefulness of the generated data for HCI research and produce data generalizations to inform post-desktop interface design.

Our goal is to develop motion capture-based biomechanical simulation as a *generic method for HCI* which can be applied without strong assumptions about specific motion capture equipment, involved types of movements, or experimenter expertise. In this thesis we want to adapt the method for user experiments in the HCI setting, evaluate the value of its output data for HCI research, and generalize the data to inform interface design.

To achieve the goal we perform *interdisciplinary research* integrating existing knowledge from the fields of human-computer interaction, computer science, physical ergonomics, kinesiology and biomechanics, and adapt it for the new environment. As a result, **in our research we use not only the generic scientific method [22] but also the methods and tools specific for each of the fields.** We use systematic cross-field *literature review* to position the proposed method in the context of the related methods and identify its advantages and disadvantages, controlled *laboratory experiments* to validate the method and evaluate its applicability limits, *simulations* to get data for relevant aspects not available from measurements, *interactive visual data exploration* to explore patterns in the data and identify specific insights, *computational and statistical methods* to build generalizations and models of the data, and *deductive and inductive logic* to derive practical recommendations and draw experiment conclusions.

Mostly we work with and draw our conclusions from *quantitative data* such as EMG, optical motion capture and force recordings, length measurements of participants' body segments, and their body weight, as well as computation and simulation results, but we use also *qualitative data* collected in questionnaires and personal interviews. To achieve generalizability of the experimental data, we recruit a diverse participant population, or in the case of detailed data collection from a single participant we validate the recorded data against the subset recordings of a set of other participants.

## 1.4 Problem Statement and Research Questions

The overarching research problem considered in this thesis is:

**How can we *efficiently design, analyze and assess high-throughput ergonomic post-desktop input methods*?**

This is a broad problem and it has multiple approaches to the solution. To be more specific, we split the problem into 3 smaller steps required to achieve the solution. These steps systematically tackle the four issues of post-desktop interface design. We state concrete research questions related to each step and answer them in the thesis.

**Step 1: *Proposing an efficient method to measure and generate performance and ergonomics data.***

In order to solve the issue of the large design and movement space, we need a method which is efficient and low-cost compared to current methods. Additionally, to understand the issues of performance and ergonomics, we need to be able to generate both types of data.

**Question 1.1: *How can we efficiently measure and generate objective performance and physical ergonomics data?***

At first, we need to identify an efficient method able to provide objective data on performance and physical ergonomics. Under "efficiency" we consider the ability of the method to generate the desired data with minimal duration, resource and expertise overhead with respect to an HCI user study without actual data collection. It needs to have low setup overhead, and require

affordable equipment, limited experimenter expertise and as little interference with the experimental task as possible.

**Question 1.2: What are the applicability limits of the proposed method with respect to a variety of tasks within HCI?**

Under “applicability limits” we understand the range of tasks for which the method can technically succeed and provide realistic results. HCI tasks are extremely diverse and cover movements of various types, amplitudes, locations, velocities, kinematic chains, end-effectors, accuracy and force characteristics. We need to identify this range of tasks which can be assessed by the method, and specify the limitations, and possible improvements of the method with respect to them, in the near future.

**Question 1.3: Does the method produce valid outputs in the HCI setting?**

We need to ensure that the method is “valid”—it provides correct data, not critically affected by noise or bias when applied in experiments with resources, expertise, scope, focus, tasks and goals common for HCI.

**Step 2: Evaluation of the usefulness of the generated data for input method research and design.**

In order to solve the issue of physical ergonomics pitfalls and provide a base for addressing the performance non-uniformity issue, we need to evaluate the data generated by the method with respect to its usefulness for HCI research and input method design. Additionally, this step provides some insights for post-desktop interface design towards a solution of the issue of absence of prior knowledge.

**Question 2.1 Does the data provide new insights with respect to input performance?**

A lot of knowledge has been accumulated in tens or even hundreds of user studies on the performance of various types of movements and through various types of devices. We need to evaluate the value of the performance data provided by the new method, whether it provides deeper insights compared to the previous knowledge and how significant the differences are.



**Question 2.2 Does the data provide new insights with respect to physical ergonomics?**

Although previously physical ergonomics was not considered deeply in HCI, there is a large body of relevant knowledge in the field of industrial ergonomics. The previous work from industrial ergonomics does not deal with post-desktop or gestural interfaces, but we still need to assess how advantageous the new method is compared to it, and whether it can provide insights beyond designers' intuition or the existing knowledge.

**Question 2.3 Does the data provide new insights concerning the relationship between performance and physical ergonomics?** The past research in performance and ergonomics was separated between the two fields. The new method should provide both performance and ergonomics data in a synchronized way, which allows joint analyses. We need to identify how large the benefits of joint analysis of the two aspects are, compared to the previous separate analyses.

**Step 3: Proposing generalizations and models of the data to inform the design on early stages without user studies.**

This step provides a solution for the performance non-uniformity issue by relating the non-uniformity with biomechanical bases. Further, this step systematizes movement space in a model towards a solution of the issue of absence of prior knowledge for post-desktop interfaces. It is demonstrated on a case of free-arm mid-air interaction and models the space reachable by the arm.

**Question 3.1 How can we reduce complexity of multidimensional joint performance and ergonomics dataset to enable a quick overview?**

As the human body is very complex system, physical ergonomics is represented by a large number of variables describing both static and dynamic loads at each body segment, and adding to this movement performance variables. In order for this data to be useful in early stages of the design process, we need a short but comprehensive and interpretable overview uncovering general patterns present in the data.



**Question 3.2 How can we model performance of movements in large non-uniform movement space?**

The post-desktop movements are highly non-uniform with respect to performance, as they are executed by various kinematic chains and neuromuscular groups. However, current movement performance models used in HCI, namely Fitts' law and its derivatives, consider the whole movement space as uniform and relate performance with only target size, amplitude and in some cases approach angle. We need to update movement performance models to be consistent with post-desktop input methods and the non-uniformity of the movement space.

## 1.5 Contributions

The goal of this thesis is to support efficient performance and ergonomics assessment of post-desktop input methods. It solves the *four issues of post-desktop input method design* in the following way:

- in order to avoid physical ergonomics pitfalls, we review the methodology of corresponding fields. We identify motion capture-based biomechanical simulation as a method providing the richest set of ergonomic variables without the need to specify the context in advance before the experiment.
- in order to be able to deal with the large post-desktop movement space, we consider efficiency of the method as well as informativeness. The motion capture-based biomechanical simulation is efficient and needs only slight overhead compared to regular Fitts' law studies.
- in order to tackle the non-uniformity of the space with respect to performance, we associate input performance with the underlying physiology executing the movement. The resulting mapping effectively produces homogeneous regions within non-uniform space, which are modeled well by simple Fitts' law.
- in order to avoid problems with sparse knowledge of post-desktop interfaces, we adapt motion capture-based biomechanical simulation as an experimental method for HCI tasks by making it more accessible for non-experts, and further lower the expertise barrier through

movement space summarization. In this way, HCI researchers and designers can more broadly apply the method without need for biomechanics expertise, and with low overhead compared to regular HCI experiments, which should result in improved coverage of post-desktop research problems and contribution towards a solid body of knowledge on post-desktop input.

Following the order of *research questions*, our contributions are made in 3 steps:

- based on review of relevant fields, we identify the method suitable for efficient performance and ergonomics assessment—motion capture-based biomechanical simulation. We adopt the method to the HCI setting, and subsequently evaluate its applicability limits and validity of outputs through two user studies.
- to demonstrate added value of the method, we apply it to real HCI tasks of touch surface analysis and comparison as well as analysis of ergonomics of tablet interaction. We perform a 40-participant user study, process the data and contribute to the research community the consolidated dataset as well as a number of its analyses.
- to inform the design of post-desktop input methods and lower the expertise barrier we create a data-driven model which integrates physical ergonomics as well as tackles performance non-uniformity—the muscle co-activation clustering. We achieve this through an extensive user study uniformly covering whole-arm aimed movements in reachable space, processing of the collected data and application of statistical learning methods.

In *the context of the HCI field* the contributions can be classified into the following categories:

- **Methodological:** We systematically review methodology of relevant fields and identify the method which bears the highest potential for the HCI field, namely motion capture-based biomechanical simulation. To adapt the method for HCI, we create a pipeline lowering the expertise barrier of its application, in two user studies we assess applicability of the method for HCI tasks and its validity in the HCI setting, and in another two experiments we consider the information provided by the method and its value for HCI.

- **Theoretical:** In most previous work on understanding users human performance was considered separately from ergonomics. In contrast to this, our work describes joint quantitative analysis of performance and ergonomics. Furthermore, to our knowledge we are the first to perform joint analysis of touch interaction with 5 various types of surfaces and directly compare them. We enrich current understanding of mid-air aimed movements by encompassing the non-uniformity of movement space into a set of equivalence classes derived using hierarchical clustering of muscle activation patterns.
- **Technical:** We develop a data processing pipeline to streamline the biomechanical simulation and allow a quick start with the method for non-experts. Additionally, together with our collaborators we create an interactive visualization tool allowing case-specific spatial interactive visualization and analysis of biomechanical, experimental and performance data using linking and brushing.
- **Design:** Our analyses contribute to design recommendations for mid-air interaction with computer vision-based interfaces, or touch interaction with public displays. Findings from the study of performance and ergonomics of touch surfaces give recommendations concerning each type of surface and can inform design of multi-surface interfaces. Furthermore, deeper analyses of ergonomics data of hand-held devices reveal that most users interact with the devices in harmful postures. We raise this problem and provide recommendations on how to avoid or improve the postures.

## 1.6 Relevant Publications

This thesis is based on and contains parts, including figures and tables, of research described in the following publications. Each reused segment is marked by footnotes. Some of the visualizations or their parts reused from the papers were created by our collaborators from the visualization group.

### Peer-reviewed:

1. M. Bachynskyi, "Physical ergonomics of tablet interaction while sitting," *Proceedings of the 39th Annual Meeting of the American Society of Biomechanics*, ASB, August 2015.

2. M. Bachynskiy, G. Palmas, A. Oulasvirta, J. Steimle, and T. Weinkauff, "Performance and ergonomics of touch surfaces: A comparative study using biomechanical simulation," *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pp. 1817–1826, ACM, April 2015.
3. M. Bachynskiy, G. Palmas, A. Oulasvirta, and T. Weinkauff, "Informing the design of novel input methods with muscle coactivation clustering," *ACM Trans. Comput.-Hum. Interact.*, vol. 21, no. 6, pp. 30:1–30:25, ACM, January 2015.
4. G. Palmas, M. Bachynskiy, A. Oulasvirta, H.-P. Seidel, and T. Weinkauff, "MovExp: A versatile visualization tool for human-computer interaction studies with 3D performance and biomechanical data," *IEEE Trans. Vis. Comput. Graphics*, vol. 20, no. 12, pp. 2359–2368, IEEE, December 2014.
5. M. Bachynskiy, A. Oulasvirta, G. Palmas, and T. Weinkauff, "Is motion capture-based biomechanical simulation valid for HCI studies?: Study and implications," *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems*, pp. 3215–3224, ACM, May 2014.

### Poster papers:

7. M. Bachynskiy, A. Oulasvirta, T. Weinkauff, and G. Palmas, "Biomechanical simulation in the analysis of aimed movements," *CHI '13 Extended Abstracts on Human Factors in Computing Systems*, pp. 277–282, ACM, 2013.

In addition to the main papers, the following papers not directly related to the thesis topic have also been published.

9. G. Palmas, M. Bachynskiy, A. Oulasvirta, H.-P. Seidel, and T. Weinkauff, "An edge-bundling layout for interactive parallel coordinates," *Visualization Symposium (PacificVis), 2014 IEEE Pacific*, pp. 57–64, March 2014.
10. A. Oulasvirta, T. Weinkauff, M. Bachynskiy, G. Palmas, "Gestikulierer mit Stil," *Informatik-Spektrum*, vol. 37, no. 5, pp. 449–453, Springer, October 2014.

11. A. Oulasvirta, A. Reichel, W. Li, Y. Zhang, M. Bachynskyi, K. Vertranen, and P.-O. Kristensson, "Improving two-thumb text entry on touchscreen devices," *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pp. 2765–2774, ACM, 2013.
8. A.-M. Feit, M. Bachynskyi, and S. Sridhar, "Towards multi-objective optimization for UI design," *CHI 2015 Workshop on Principles, Techniques and Perspectives on Optimization and HCI*, Seoul, Korea, April 2015.
9. M. Bachynskyi, "Towards biomechanically-inspired index of expert drawing gestures complexity," *CHI 2014 Workshop on Gesture-based Interaction Design: Communication and Cognition*, Toronto, Canada, pp. 65-68, April 2014.

## 1.7 Thesis Structure

The thesis is structured according to the order of the research questions:

- In **Chapter 2** we consider **Research Question 1.1** by providing a broad overview of the related work.
- In **Chapter 3** we continue with **Research Question 1.1** by describing methods of motion capture-based biomechanical simulation and the adaptations necessary to apply it for HCI tasks. We describe the pipeline, which integrates both performance and ergonomics assessment within a single dataset, and tools developed for its analysis.
- In **Chapter 4** we consider **Research Question 1.2** by describing a user study aimed to assess applicability limitations of the method for 5 HCI-specific tasks.
- In **Chapter 5** we consider **Research Question 1.3** by validating the method outputs against ground truth muscle activation data, recorded as EMG for full-arm aimed movements.
- In **Chapter 6** we consider **Research Questions 2.1, 2.2 and 2.3** by providing examples of the application of biomechanical simulation for analysis of 3 different tasks, and highlight the value added by the method.

- In **Chapter 7** we consider **Research Questions 3.1** and **3.2** by describing a compact summarization of the whole movement space of the arm using muscle co-activation clustering. Based on this summarization, we approach the non-uniformity of movement performance.
- In **Chapter 8** we summarize the research described in this thesis in the context of research questions and propose future research directions to improve the method.

# Chapter 2

## Background & Related Work

The work described in this thesis bridges the fields of *HCI* with *Ergonomics*, equips input method designers with powerful tools from *Biomechanical* research, and makes *Biomechanical Modeling and Simulation* more accessible for non-expert users. It proposes an efficient method to assess performance and physical ergonomics of post-desktop input methods, evaluates its applicability and validity in the HCI setting, demonstrates the value added by the method, and to further lower the expertise barrier, develops a summarization of a whole-arm movement space through a muscle co-activation clustering.

This chapter provides background on the state of the art of each relevant field and highlights new insights gained in this thesis. In order to provide context on the current state of the HCI field, we describe, in the first section, general approaches of input method design, principles and goals of traditional input method design, and the specifics of post-desktop input methods. We highlight user performance and physical ergonomics as two of the most important design objectives, and describe the methods and models to assess them in more detail in the next 2 sections. We pay special attention to previous digital human simulations in HCI and ergonomics, as they are the closest ancestors of the biomechanical simulation within these fields. We provide background on motion capture-based biomechanical simulation by describing the state of the art of biomechanical modeling and simulation, including the established practices and methods, their explored limitations and general validity. In this way we provide a basis to answer **Research Question 1.1**. Further, we describe previous approaches of summarizing biomechanical data and extracting higher-level features using machine learning methods. Finally,

we put the work performed within this thesis into perspective with the existing knowledge and highlight its novelty and overall gains.

## 2.1 Input Method Design

Input method design is an area within HCI which deals with shaping and development of information transfer methods from the user to a computing system. Over more than 30 years the HCI field has established standard practices, rules and processes to design user interfaces for personal computers [23]. However, the traditional methods turn out to be inefficient for design of input methods “beyond the desktop”, for example for vertical touch displays, mid-air or full-body gestural input methods. One of the main reasons for this is that in the past the task of input method design was split between two fields:

- Industrial design dealt with design and development of hardware and physical input artifacts, for example mice, keyboards or joysticks, and their appropriate physical ergonomics assessment.
- Human-computer interaction dealt with cognitive and information processing aspects of computer input in software, for example transfer functions, menu hierarchy, control elements placement on the display, etc., and analysis of their usability in terms of effectiveness, efficiency and satisfaction.

The input artifacts for traditional input methods usually constrained movement types and ranges to a small area, which allowed thorough analysis of physical ergonomics. Further, the HCI field benefited from limited movement space of the artifact, as it provided a good basis for the input space uniformity assumption, necessary for user evaluations, as well as development and application of user performance models.

In contrast, post-desktop input methods do not constrain movement space, and as a result give more movement freedom to users, challenging designers. The designers have to deal simultaneously with both cognitive as well as biomechanical properties of an input method. For example, when designing a mid-air gesture the designer has to consider movement ranges, physiological loads and fatigue as an ergonomics expert, and learnability, cognitive load, memorability and errors as a HCI expert. Additionally, the physiological and cognitive properties of an input method interleave when looking at efficiency and satisfaction.



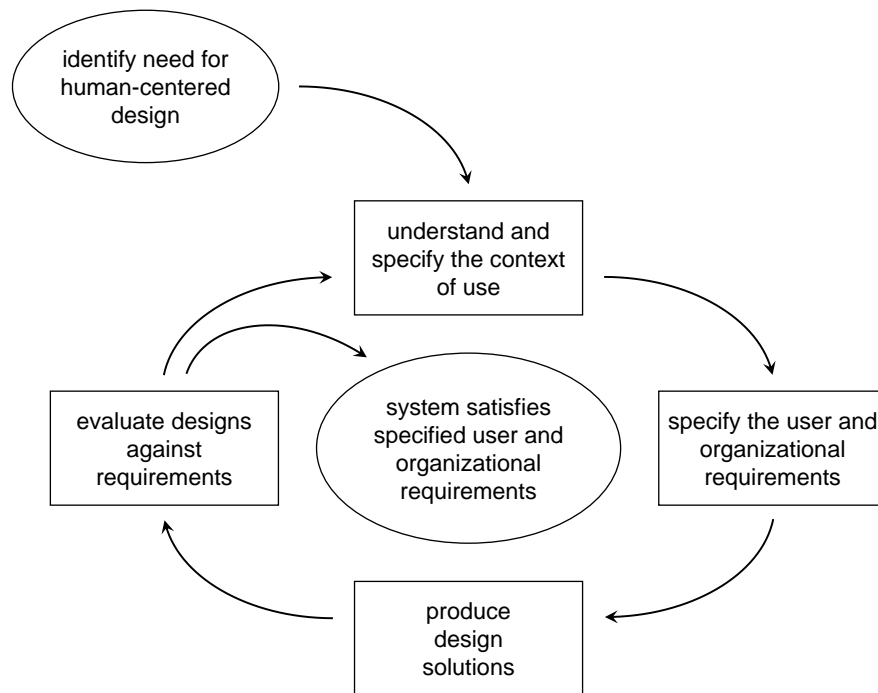


Fig. 2.1: User-centered design process [24]

### 2.1.1 Design Process

Since its establishment as a separate field, HCI has developed a number of design methods, approaches and processes, the most effective of which are documented as international standards [4, 24, 25]. As even the greatest products and systems can fail if they do not meet user needs, the user is often recognized as a central person in the design, for example in user-centered design (UCD) [16, 26, 27], or participatory design [28, 29] approaches.

UCD is a design process which deeply involves end-users throughout the whole period of shaping and development of a product, which makes it possible to define and meet multiple design goals: matching a user's conceptual model and his knowledge, skills and capabilities, and providing consistency, useful and informative feedback, error recovery and simplicity. UCD ensures that a product can be used by the end-users to achieve their goals with effectiveness, efficiency and satisfaction in the specified context of use, or in other words, UCD ensures good usability of the product. It is one of the most effective design processes, and that is

why it has become an international standard [4,24]. As can be observed in Figure 2.1, UCD consists of multiple iterations of 4 activities [16,24]:

1. understand and specify the context of use,
2. specify the user requirements,
3. produce design solutions,
4. evaluate designs against requirements.

In the first step designers need to understand the user and his tasks and context of use, so they perform research with real people representing a prospective user population. The designers apply ethnographic study, contextual inquiry, prototype testing, or other methods, or careful analysis of similar products if available. In this way the designers gather necessary information to understand real user problems, tasks, needs, and the context in which they emerge.

After the context is specified, the next step is to establish the user and organizational requirements. The requirements need to cover multiple aspects of the system and define trade-offs between them: system performance, development and operation cost, legal requirements with respect to safety and health, interaction of multiple users and stakeholders, users organizational task requirements, user performance, integration and learning cost, maintenance cost, workstation design and interface design.

In the third stage the design ideas are generated and further implemented in the system prototypes. The designers have to take into account previously specified requirements and widely accepted user interface design principles [16,23]. The prototypes imitate functionality of the final system to present it early to users for their feedback. The prototypes can be of different fidelity levels, from simple sketches to imitation of the working system through the “Wizard of Oz” technique [16].

The fourth stage is evaluation of the prototypes, ideally with potential users through usability testing. The users are presented with the prototype as a working system and asked to complete a set of typical tasks. During the experiments users are observed by the researchers, who collect a range of qualitative and quantitative data. If a product was already deployed, the data can be collected directly in real use by user population

by providing an alternative design to a subset of users. This data is further used to identify deficiencies of the interface, and as input for design refinement.

There are a few design processes close to UCD, for example human-centered design [30,31], activity-centered design [31,32], and goal-directed design [33,34]. They differ mostly in the focus of the design process, but the process itself stays close to the UCD and contains similar steps, involving user research, analysis and evaluation.

While UCD is a widely used and effective design process, it still has its deficiencies; for example, the cost of prototypes and user studies can be high, the participants of user studies can poorly represent the user population, and the design process can take a considerable amount of time, increasing time-to-market and posing a risk of losing against competitors. For this reason, considerable effort was invested by the research community into model-based interface design and development of generalized human models, which can provide cheaper, more accessible and information-rich alternatives to inform input method design [35–37].

The user models can serve two purposes: first, they provide relevant analytical information on the user research stage, and second, they help to evaluate prototypes without performing user experiments. Most models within HCI describe users' cognitive processes and information processing performance to complete a task, for example GOMS [38,39] or KLM [40]. Additionally, all operations within a cognitive model of a task are represented by operation-specific models, for example movement performance models such as Fitts' law [41], selection time models such as Hick-Hyman law [42] or power law of practice [43], etc. The domain-specific models from the ergonomics field estimate postures [44,45], physiological loads within the body [46,47], injury risks [48,49], energy expenditure and muscular fatigue [50,51], etc. Similarly as GOMS aggregates operation-specific models in HCI, the ergonomic models are aggregated into complex Digital Human Models [52,53]. We provide more details on the existing models in Sections 2.3 and 2.4.

Both UCD and model-based design have their pros and cons, and typically are applied interchangeably depending on a stage of product development [23]. That is why the goal of this thesis is to support efficient evaluation of physical ergonomics together with performance of post-desktop input methods on both early and late stages of the design process within UCD and model-based design.

### 2.1.2 Performance & Ergonomics—Key Objectives of Input Method Design

UCD and usability evaluation ensure achievement of requirements and goals set up for a particular product. The exact goals differ for each product, but usually they systematically cover a few categories. As defined by ISO9241-11 [25] these categories are effectiveness, efficiency and satisfaction. Nielsen defines 5 categories: learnability, expert user efficiency, memorability for infrequent users, frequency and seriousness of human errors, and subjective user satisfaction [54]. Quesenbery proposes another formulation, 5E: efficient, effective, engaging, error tolerant and easy to learn [55]. These formulations cover the same range of aspects, with slight differences between category details.

Each category is assigned a priority, depending on the actual user interface and application. When focusing on an input method which is used regularly for prolonged periods, two goal categories naturally get high priorities: performance and ergonomics.

Input performance closely corresponds to the above-mentioned efficiency category and additionally contributes to satisfaction, as reaching high input performance in a task improves user satisfaction. Performance is the most important factor in technology acceptance models for professional use [56–58], and one of the most important factors for hedonic-motivation systems acceptance models [59]. These models quantify whether the user population will adopt or ignore a particular technology.

The physical ergonomics category is orthogonal to the usability categories listed above and contributes to most of them, for example an input method with poor physical ergonomics would fail even if it is intuitive, easy to understand and efficient. The best example for this is Light Pen, which was considered as the “mouse killer”, but failed in user adoption due to poor physical ergonomics, namely due to high fatigue levels [60].

## 2.2 Body of Knowledge in Desktop and Post-Desktop Interface Design

In the next sections we present an overview of the current body of knowledge with respect to performance and ergonomics for traditional input methods, touch-based and mid-air interfaces. The overview of traditional

## 2.2. Body of Knowledge in Desktop and Post-Desktop Interface Design

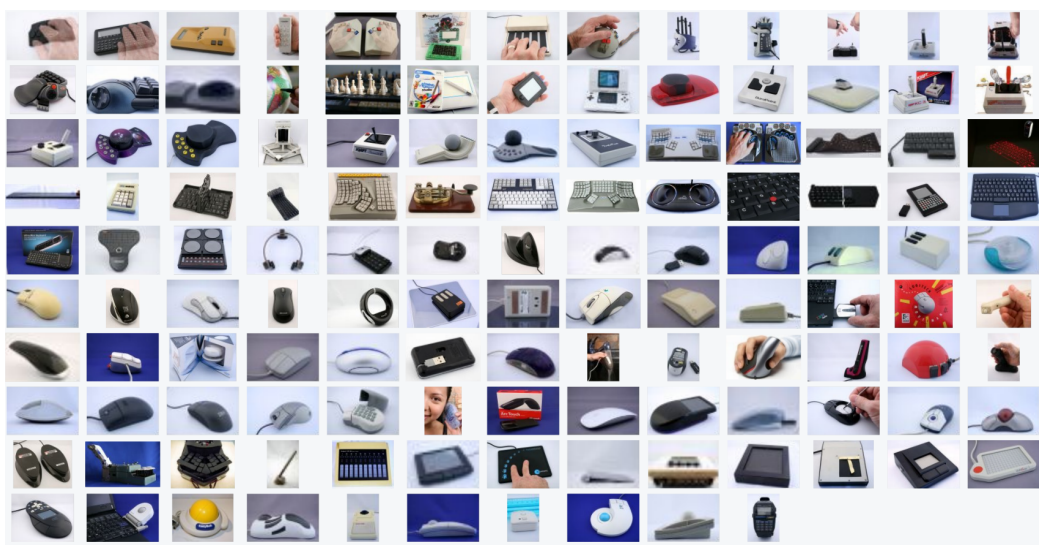


Fig. 2.2: Collection of traditional input devices [61]

input methods we provide as a baseline, to highlight the research deficit in post-desktop input methods. This thesis contributes to the knowledge on both touch-based and mid-air input methods through novel user studies, datasets and analyses.

### 2.2.1 Traditional Input Methods

Traditionally HCI was focused on interaction with personal computers (PCs) using physical input artifacts such as a keyboard, mouse, joystick, touchpad, trackball, etc. (Figure 2.2). At that time the tasks of ergonomics and performance assessment were split between two fields: HCI and industrial design. Both fields have developed corresponding methods, which rarely intersected in research, and even if they intersect, it is not particularly deeply—every paper has a clear focus within its own field, and can only briefly mention some concerns related to the other field. So it is logical to describe the related work as split into two parts: physical ergonomics and input performance.

#### Physical Ergonomics

Since the penetration of personal computers into the work environment, they became the object of interest for a multitude of physical ergonomics works [62]. Each of the papers either covers work with personal com-

puters in general [63–65], or is focused on musculoskeletal health effects of interaction using a particular computer form-factor [66–68] or input device, such as a keyboard [69–71], mouse [72–74] or touchpad [75]. A large fraction of works are questionnaire-based, but they often cover impressively large user populations, from a few hundred [76,77], up to a few thousand [72,78]. Fewer works are based on user observations [79] and objective measurements of videometry [68,80], goniometers [68,81], EMG [74,82,83], grip and interaction forces [74,84], or even pressure inside the carpal tunnel [81].

Concerning interaction with personal computers in general, it has been found that total time of interaction per day or per week is associated with higher risk of musculoskeletal disorders of the neck, upper back, shoulder and arm [64,76], in particular for females [63,65]. Additionally, muscle activity of the upper back and shoulder muscles is increased under high mental demands [82], which also increases the risk of corresponding musculoskeletal disorders [77]. Prolonged computer use is particularly problematic for musculoskeletal health of children [78,85], as all of them use incorrect postures [79] at computer and further adopt them habitually [86]. Researchers have developed corresponding ergonomics models [87] and guidelines [69,88–90] describing workplace setup and activity patterns, which, when adopted, should reduce musculoskeletal risks during computer work.

Concerning individual device types, laptops are disadvantaged comparing to desktops, as individual input and output components cannot be detached and adjusted, thus leading to a non-optimal workplace setup and particularly bad postures when used on the lap [66–68]. Computer mouse usage increases loads, muscle activity and contributes towards musculoskeletal risks for the neck, shoulder, arm and forearm due to increased arm abduction [91]; as well, it is tightly associated with carpal tunnel syndrome in the case of extensive use [72,81]. Ergonomic vertical mouse designs [73] or alternative pointing devices [83,92] provide lower musculoskeletal loads, pose smaller risks and can even lead to improvement of existing musculoskeletal disorders [73]. The musculoskeletal loads and muscle activity posed by computer keyboards are lower than those of mice [82], but they still contribute to musculoskeletal disorders or pain in the upper back, neck and wrist [69]. Ergonomic split keyboards, when placed below elbow height with correct tilt angle and used jointly with arm support, reduce musculoskeletal loads, risks and pain [69,71,80,93,94].



Decades of ergonomics research concerned with traditional input methods have resulted in the desktop workspace with traditional input devices optimized according to the established ergonomic recommendations; this can significantly reduce or even minimize risks of various musculoskeletal outcomes. However, even in this highly studied area, motion capture-based biomechanical simulation can contribute by providing quantitative data for different design alternatives; for example, it can show how great a reduction in musculoskeletal stress we can get when using a tilted mouse or split keyboard instead of the standard ones.

### **Input Performance**

Input performance of traditional interfaces was extensively studied, even more broadly than physical ergonomics. For example Soukoreff [95] lists 24 papers just for non-standard Fitts' law modeling of mouse input performance, leaving out performance evaluation with the standard Fitts' law as well as performance evaluations using movement time directly and skipping Fitts' law entirely. Works analyzing keyboard performance are found even before the development of computers, instead addressing typewriters [96]. Already back in 1972 Kroemer [97] describes a number of related works dealing with the effect of different keyboard design factors like key arrangement, physical keyboard layout and orientation on user typing performance. While early works on both keyboard and mouse use task completion time as a measure of performance [60], since the end of the 70s performance measures of both types of devices essentially come down to Fitts' law modeling [8,98].

Performance of multiple devices and various aspects of interaction in pointing tasks were analyzed in a large number of comparative studies, most of which use Fitts' law [95]. These studies covered mouse, jump key, tablet, stylus, touchpad, trackball, trackpoint, joystick, knee control and custom input methods in studies of pointing, dragging, text selection, scrolling & pointing, and trajectory-based tasks [98–103], as well as combinations of these devices and custom 6DOF devices for computer input in 6DOF tasks [104,105]. Most of the studies cover adult subjects, but a few of them also consider children [106,107]. While the results of some studies contradict others, in general there is an agreement that pointing is faster than dragging [100], and the mouse is the fastest for dragging, while it provides performance similar to tablet and stylus in pointing [100]. The light pen performs better for novice users, while the

mouse is better for experts [60]. Some works conclude that the mouse is close to pure eye-hand tasks with respect to performance, so there is not much possibility for improvement over it [98]. Concerning performance between different mice there is no agreement: while Isokorski [102] found performance of different mouse types to be comparable, Han has found Apple mice to perform better than others [108]. Joysticks are usually worse than mice for pointing tasks [60,109], but can complement them better than a scroll wheel for scrolling & pointing tasks [110]. Multiple studies also considered various aspects of interaction. Users can interact with pointing devices using both the dominant and non-dominant hand with similar performance, excluding small targets, for which the dominant hand performs better [101]. Mice with higher gain show higher performance for all but small target tasks, but this can be improved by using cursor acceleration [111]. Interaction using the fingers provides 30% higher performance than using the hand only [104]. For trajectory-based tasks, the mouse performs similarly to a tablet, trackpoint, a touchpad, but trackballs perform worse [112]. It has been shown that extrapolation of mouse interaction principles to 3 dimensions, namely a “flying” 3D mouse, provides the best performance in 3D docking tasks [105].

While pointing is an important part of interaction with any computing system, it is limited by pointing performance of the user as described by Fitts’ law. Often researchers tried to exploit effects of individual Fitts’ law parameters to reach higher performance using software-based techniques to dynamically increase the size of or decrease the distance to the potential target, for example pie menus, potential targets mapped next to the cursor, object pointing, area cursors, expanding targets, dynamic adjustments of control-to-display gain, semantic widgets, etc. While these techniques work well in some specific artificial cases, they do not provide benefits in real interaction [113].

Research on text entry has found that the keyboard design can be significantly improved with respect to performance by adopting different physical designs (split keyboard, rotated segments for each hand) [114], or character mappings [115]. Despite a large amount of research analyzing keyboard performance, and wide knowledge of drawbacks of QWERTY compared to optimized designs [116,117], or even DVORAK [96], it still is considered as standard, with only a small fraction of users switching to other keyboard types.

The method proposed in this thesis can contribute to analysis of performance of traditional input methods by providing direct instead of



device-mediated user performance in movement-based tasks. Additionally, it can provide direct mapping between performance and physical ergonomics or underlying musculoskeletal structures, and quantify the corresponding effects.

### 2.2.2 Touch-Based Input Methods<sup>1</sup>

Advances in capacitive sensing technology accelerated the development and integration of touchscreens in a range of interactive devices, from touch-based ticket and banking terminals, interactive tabletops, public displays, and in-car systems, to multimedia players, tablets, smartphones and smartwatches. As a result, billions of touchscreen devices are sold and regularly used worldwide [119].

While the UCD is formulated as a general and abstract process which can be applied to a variety of design tasks, including design of touch-based input methods [120, 121], there are a number of important considerations which have to be taken into account for the design of usable touchscreen applications. In contrast to keyboard- and mouse-based interaction, which were extensively studied for both ergonomics [69–74] and performance [95, 98, 100, 110] over more than 30 years, touchscreen devices reached the market so fast that extensive analyses have not been performed.

We review previous work from two areas: physical ergonomics and performance, two areas which have rarely intersected in previous work.

#### Physical Ergonomics

Studies of physical ergonomics in touchscreen interaction have looked at comfort, user preferences, joint angles, postures and muscle use. Each study has focused on a particular type of surface.

Müller-Tomfelde et al. [122] collected user preferences for touch display workspace design. They found that the majority of participants preferred a tilted display at 45° or 30° angles to horizontal or vertical configurations. They explained this preference by better visibility and reachability of the display, improved comfort for the visual system and body posture. Barbé et al. [123] simulated postures for interaction with different touch displays in an airplane cockpit. They validated the models

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<sup>1</sup>This section is based on the paper *Performance and Ergonomics of Touch Surfaces: A Comparative Study Using Biomechanical Simulation* [118]

using motion capture data and a simple digital human simulation, CA-TIA/HUMAN. The location and orientation of the display had a strong influence on physical effort. In particular, it needs to be taken into account for prolonged tasks taking longer than 60s. Davis et al. [124] analyzed data entry comparing touchscreens to physical keyboards. They found that a touchscreen is equal to or better than a keyboard in terms of kinematics, discomfort, usability, and error rates. A tilted orientation was preferable to a horizontal or vertical orientation, an effect that was influenced by both physical and visual ergonomics [125]. The authors conclude that the biomechanical analysis was limited, as a deeper analysis of physical loads *inside* the body could not be performed. Young et al. [126] assessed postures and muscle activity in the shoulder and forearm during tablet interaction. They had several findings: the wrist is often operating in close-to-extreme angles, the forearm extensor muscles are highly activated in text entry, the trapezius muscles have higher activation when the tablet is on the table, and the anterior deltoid has high variance when the tablet is heavier. Kim et al. [127] analyzed smartphone interaction and found that the body posture (sitting, standing, sitting at a desk) affects the range of motion and the muscle activity of the thumb. They concluded that deeper analyses of ergonomics are necessary in future work.

In this thesis we apply motion capture-based biomechanical simulation to the analysis of 5 different touch surface form factors: public display, interactive tabletop, laptop with touchscreen, tablet and smartphone. To our knowledge, this is the first work which considers these 5 surfaces in a comparative user study using within-subject design, creates such a rich dataset describing corresponding musculoskeletal loads, quantifies strengths and weaknesses of each surface type, and highlights the main risks, namely stressful neck posture in 95% of participants in interaction with a tablet.

### Input Performance

Touch input has been found to be advantageous but also challenging when compared to mouse and keyboard [128, 129]. Touch lacks the haptic feedback of a physical button, and it suffers from occlusion and the fat finger problem. However, it performs relatively well in pointing tasks that involve medium-sized and big targets. Due to its directness it has additional advantages for novice users [128, 130].

Multiple studies have analyzed input performance with touch surfaces. However, as noted, most exclusively focused on a particular device [130–133]. We are aware of only a single publication comparing different types of surfaces. However, it analyzes only reading comfort and performance [134].

Many previous studies look at accuracy. Beringer et al. [135] analyzed response times and accuracy on vertical touch displays, finding them to be non-uniform with respect to the target location and to the angle between line-of-sight and the screen. They also modeled input offsets between touch points and targets, which improved the accuracy of touch for a particular participant. Park et al. [133], similarly to Beringer et al., assessed the accuracy of single-thumb interaction with a smartphone. They found that distributions of touch points are Gaussian and distinct for each participant, button location, and size. Similarly, Parhi et al. [136] reported touch accuracy limits for PDAs, recommending minimum target sizes of at least 9.2 mm for single target tasks and 9.6 mm for multi-target tasks. Wang et al. [137] analyzed the touch area for all fingers on a tabletop and extracted touch area properties as shape, size, and orientation. Holz et al. [138] analyzed human errors while using touch and concluded that the origin of errors is not the fat finger problem, but the perceived input point, which they model based on roll, pitch and yaw. Their projected center model [139] performs significantly better than the standard method, decreasing input offsets to as low as 1.6 mm.

A large number of other studies investigate input performance in general, taking speed into account. Most of the analyses have used Fitts' law modeling [95]. Sears et al. [130] found that direct touch outperforms mouse input on a vertical touchscreen when pointing to targets larger than a single pixel. With additional stabilization, the performance was the same and the error rate for 4 pixel and 1 pixel targets significantly decreased. Micire et al. [131] confirmed the suitability of Fitts' law models for horizontal tabletops. The study found that touch performs better than mouse input for all but 10mm targets; however, for 10mm and 20mm targets, the error rate was higher for touch input. Kin et al. [132] found that any touch-based method outperforms mouse input in a multitarget selection task, while the difference between multitouch and touch is very small. Sasangohar et al. [140] found that direct touch input on a tabletop provides significantly better performance for most targets in a tapping task, although it has the worst error rate for the smallest targets. Po et al. [141] compared pointing performance of mouse and direct touch in-

put in the upper and lower visual field of a large vertical display. Oehl et al. [142] compared pointing with a stylus to the same target setup on touch displays of different screen sizes. Their surprising finding was that for difficult targets (small, distant) the participants performed better on bigger rather than smaller displays.

With respect to performance, similarly to ergonomics, this thesis contributes joint analysis among 5 surface types. Although the underlying interaction principle—direct touch—is the same for all surfaces, we have found performance differences of up to 30% between them. Our joint performance-ergonomics analysis can shed light on the relationship between them for different surfaces, in particular between performance and energy expenditure represented by total muscle activation.

### 2.2.3 Mid-Air Input Methods

Development of IMU-, camera- and depth-based motion tracking and gesture recognition technology allowed human-computer interaction to be shifted beyond the desktop and touch into mid-air. A large number of recent works propose mid-air interfaces, which bring benefits to users where touching a computer is not acceptable (medical setting, surgery), regular 2-D touch interaction is not comfortable (large display environments, 3D interaction, remote interaction, smartwatch interaction), touch interaction is not hygienic due to too many users (outdoor interactive public displays), specific movements are desired (rehabilitation, exergaming), the movements provide a more natural communication channel (human-robot interaction), or mid-air interactions better map to physical world movements and could be more fun (sports games for Microsoft Kinect, PlayStation Move, Nintendo Wii) [143–149]. Unfortunately, most current papers propose an interface or interaction technique without proper evaluation and possibility to put them into context with other works with respect to ergonomics and performance. For ergonomics evaluation usually only subjective measures are used, while performance is commonly evaluated either by movement time, by words per minute for mid-air text entry, or by the classical Fitts' law, which does not perform well for large mid-air movements due to non-uniformity.

### Physical Ergonomics

Only a few works related to mid-air input consider physical ergonomics of an interaction. Hincapié-Ramos et al. [150] proposes the consumed endurance metric for assessing fatigue of mid-air input. It is based on Rohmert's law and moment at the shoulder joint, and represents simplified biomechanical simulation computed on Microsoft Kinect output with integrated joint torque bounded from above. The authors have validated the method against a Borg CR10 scale and demonstrated how to apply it for HCI tasks. While this method of course provides some insights on fatigue and physical ergonomics, it still lacks predictive power due to simplifications considered in computation, and it does not consider muscles. Another work used the NASA Task Load Index to assess workload of users during mid-air interaction with and without feedback [151]. The results showed that presence of feedback improved all scores of the NASA TLX and could potentially reduce fatigue in mid-air interaction. A third work considers input performance with respect to perceived comfort of a mid-air interaction in various regions [152]. In a first study 27 participants rated their comfort in 26 arm postures. Then a pointing study with another 21 participants was performed with aimed movements in each of 26 postures, but the results did not show a significant difference in performance between comfortable and uncomfortable postures.

The method described in this thesis makes it possible to perform efficient quantitative analysis of physical ergonomics in mid-air interaction both in user studies as well as using the proposed clustering. We demonstrate its effectiveness on an analysis of mid-air aimed movements and corresponding virtual keyboard and camera-based smartwatch interaction by identifying optimal mid-air keyboard placement and smartwatch camera orientation.

### Input Performance

Few works assess input performance in mid-air input. Özacar et al. [153] compare direct 3D object manipulation with a 2D cursor-based pointing technique for 3D docking task and find that direct manipulation, while being slightly faster than the baseline, suffers from larger error. Erazo et al. [154] create a KLM-based performance model for mid-air interaction. They estimate model parameters in a user study, and then validate it in 3 user studies and 14 tasks. Winkler et al. [155] investigated mid-air interaction with projector phones, and found that interaction in mid-air behind

the phone provides the best performance, but a higher error rate compared to the interaction in “touchpad” or user-elicited modes. Wagner et al. [156] investigated performance of simultaneous pointing to a target on a wall display and to a particular body part. They found that the compound task was significantly slower than pointing alone, as pointing to a body part was affecting balance either of the whole body, or of the pointing arm. A few studies also look at performance of pointing-based mid-air text entry methods for large wall displays [157–159]. However, they do not look at individual aimed movements and do not use Fitts’ law performance measures. The only measure they use is aggregated words per minute.

Our method allows analysis of movement performance in mid-air tasks using Fitts’ law and relation of performance to underlying muscle groups. In this way the large, non-uniform with respect to performance movement space can be split into uniform regions, within which Fitts’ law can be successfully applied. In this way it provides a more task-independent performance measure. We use our method to create a performance map of the whole reachable space based on muscle co-activation clustering, and apply it to the analysis of mid-air keyboard placement.

### 2.2.4 Discussion

Input method design approaches rely on assessment of physical ergonomics and performance either in usability evaluations or in model-based evaluations. While traditional input methods were centered around physical artifacts, the movement and design space were small enough for fast evaluation of physical ergonomics within one field and then evaluation of performance within the other field. It was possible to analyze small design and movement space using a wide range of methods, as reported in tens of relevant user studies. However, with post-desktop input methods the situation changes quite radically: the movement space is huge and both performance and ergonomics have to be considered within the field of HCI; as a result, the traditional methods are inefficient and additionally there is a lack of ergonomics expertise. Therefore the amount of research in assessment of post-desktop input methods is much smaller than for traditional input devices, which is reflected in the reduced number of related works when moving from traditional input methods to touch-based input methods and further to mid-air input methods. In particular for

mid-air input methods this results in poor designs, a number of large industrial failures and current stagnation in the field.

Our goal is to propose new efficient methods allowing joint analysis of performance and ergonomics, which could accelerate the research, development and testing of post-desktop interfaces and design ideas.

## 2.3 Physical Ergonomics

Ergonomics is the scientific discipline concerned with the understanding of interactions among humans and other elements of a system, and the profession that applies theory, principles, data and methods to design in order to optimize human well-being and overall system performance [9]. Physical ergonomics is a subfield of ergonomics which considers human anatomy, physiology and biomechanics in relation to physical activity. Physical ergonomics principles and methods are widely used in industrial design, but not yet in HCI. In this section we summarize existing physical ergonomics practices, tools and methods used in research and design. We highlight possibilities and deficiencies of these methods for applications within HCI.

### 2.3.1 Physical Ergonomics Data Collection Methods

In the past, the physical ergonomics field was concerned mostly with workplace analysis and design, so it has established a number of corresponding assessment methods. A large fraction of them is applied directly at the workplace in order to capture regular activities of the workers without artificial disturbances. All these methods can be categorized into 3 groups: self-reported discomfort questionnaires, workplace observations and direct measurement-based methods [160, 161].

#### Discomfort questionnaire methods

Discomfort questionnaire-based methods provide rough qualitative data about the risks at the workplace and are the most straightforward to apply. It is generally accepted that the discomfort at the workplace is the first sign warning of musculoskeletal injury. If the discomfort is ignored, after prolonged exposure it can lead to experience of pain caused by minor trauma. If further ignored, it can lead to serious musculoskeletal injury or disease, as for example repetitive strain injury, carpal tunnel



syndrome or arthritis [160]. As discomfort is a subjective experience of a user, it can only be assessed by asking the user about it, either in an interview or by filling a questionnaire.

All questionnaires are based on previous work in the ergonomics field and reflect the state of a particular society's requirements for musculoskeletal safety at the workplace. The most prominent discomfort questionnaires are Standardised Nordic Questionnaire [162], PLIBEL [163], NIOSH [164] and the Dutch Musculoskeletal Survey [165]. They consist of a set of questions systematically covering postures, movement types and their temporal characteristics. The health risk areas are identified based on all responses, and are then investigated in detail by observation or measurement-based methods.

The questionnaires contain various types of questions: binary, categorical and ordinal. While binary or categorical results are straightforward to interpret, ordinal results need special analysis and interpretation. Ordinal questions commonly assess perceived levels of exposure, discomfort, exertion, workload, stress, etc. on a rating scale. The most common in all areas are 5- or 7-level Likert scales [166], and within ergonomics the Borg Ratings of Perceived Exertion (RPE) and Borg Category-Ratio 10 (CR10) scales [167]. In contrast to purely ordinal Likert scales, Borg RPE and Borg CR10 provide mappings of verbal anchors to numerical values on a linear scale, allowing application of standard statistical methods.

While a variety of questionnaires are often applied in HCI studies, discomfort questionnaires are poorly suited for them. The reason is that these methods are oriented toward workers regularly exposed to the risk factors for a long enough period to develop a discomfort, while the common HCI studies are not prolonged enough, making the results unreliable. Additionally, even with long exposures the results are subjective, need a large number of participants to be statistically significant, and lack validity and reliability.

### **Posture observation methods**

Posture observation-based methods allow expert ergonomists to gather objective qualitative data about the risks at the workplace without disturbing the workers or influencing their activities. These methods are based on the fact that the observable human posture reflects the musculoskeletal activity of the whole body. It is assumed that there exists a safe "neutral" posture, and deviations from it impose risks on the mus-



culoskeletal system proportional to the angle, frequency and duration of exposure. In contrast to discomfort questionnaires, this method allows possible risks to be identified even before the discomfort can be perceived, providing applicability in short-term studies for interface design. The assessment is performed by ergonomics experts either by direct observation of the workplace or by analysis of video recordings [168].

The most important and widely used methods from this category are Rapid Upper Limb Assessment (RULA) [169] and Rapid Entire Body Assessment (REBA) [170]. Similarly to questionnaires, they systematically cover regions of interest (RULA) or the whole body (REBA) and allow ergonomics experts to quickly perform event-based assessments of users' postures. Additionally, they support the ergonomists in rating the postures by visualizations of postural schemes. Further, all posture segment ratings are summarized through table computations into a single risk assessment score.

Another method, the Strain Index (SI) [171], includes into the assessment, besides possible postures of the arms below the elbow, also the observed exertion levels in each posture and temporal features of the activity, such as duration of exertion, percentage of task cycle in exertion, frequency of exertions and total time on the task per day. While part of the data necessary for SI is quantitative, it is still split into few categories and provides only qualitative results.

A number of other methods within this category were developed and used for ergonomical analyses of workplaces, for example the Quick Exposure Checklist [172], Ovako Working posture Analysis System (OWAS) [173], posture distribution-based RULA [174], the Portable Ergonomics Observation (PEO) [175], OCRA Index ([176]), etc. However, they are similar to the above-described RULA, and REBA, or SI, use the same principles and assumptions, so we do not describe them here.

In contrast to discomfort questionnaires, the observation-based methods can be applied in HCI for injury risk assessment in research and on early stages of input method design. In this way major design faults, in particular for gestural interfaces [177], can be avoided at relatively low cost. The downside is that application of these methods demands special skills from the investigators, which are commonly out of scope of HCI expertise. Although the data avoids subjective variability of each individual worker, it is still subjective with respect to an ergonomics expert performing the analysis. As a result, these methods provide only imprecise qualitative results concerning presence or absence of the health risks

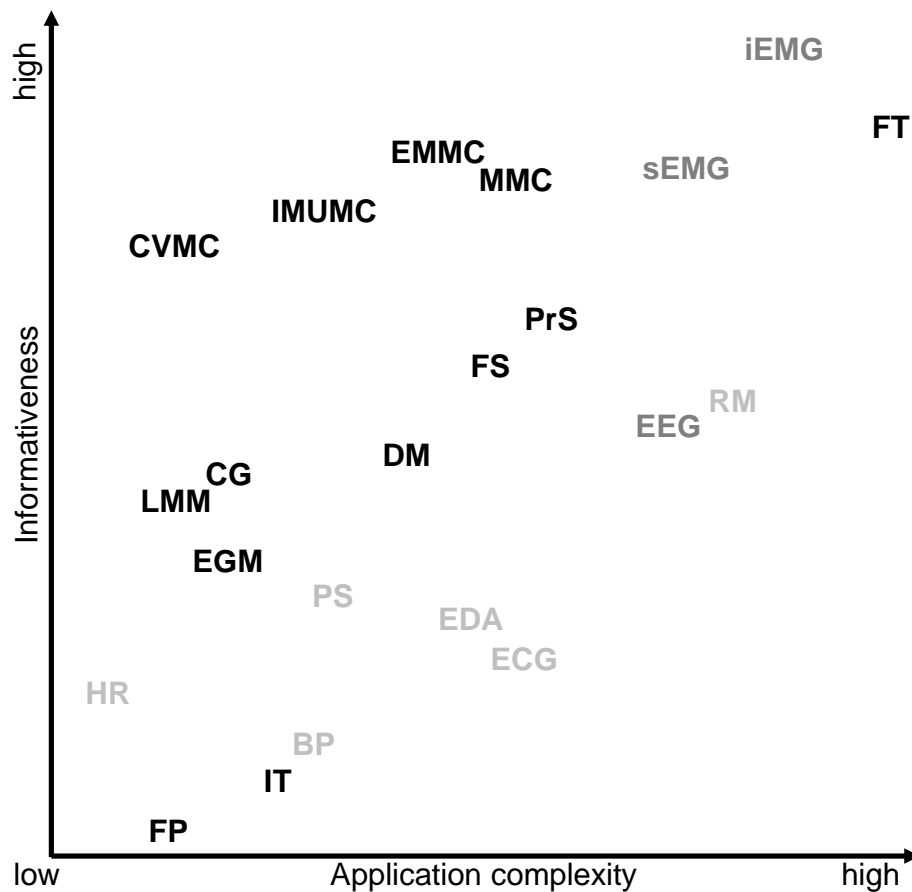
and usually require following more detailed analyses to reduce the risk. While health risk assessment is of course important for success of input methods, the observation-based methods still lack the power to provide information about effort and fatigue, which are particularly important for HCI.

### Direct measurement methods

Direct measurement-based methods are the most comprehensive, informative and accurate, albeit the most resource intensive. They provide rich quantitative data, measured directly in the human body, which describes most physiological and even some cognitive and emotional states and processes. Depending on the type of data recorded in the experiment, the direct measurement methods can be further split into 3 broad categories:

1. methods which consider *mechanical processes* inside the human body, for example computer vision (CVMC) [178–181], electromagnetic (EMMC) [182], mechanical (MMC) [183] and inertial motion unit-based (IMUMC) [184] human motion capture, electronic goniometry (EGM) [185–187], hand kinematics recording by CyberGlove (CG) [188, 189], trunk kinematics recording with Lumbar Motion Monitor (LMM) [190], force recording within the musculoskeletal system with force transducers (FT) [191], isometric [192, 193], isotonic [194], and isokinetic [195, 196] dynamometers (DM), as well as external force recording with force plates (FP) [181], instrumented treadmills (IT) [197], force sensors (FS) [187, 198] and pressure sensors (PrS) [199–201];
2. methods which consider *electrical processes* inside the human body, for example surface (sEMG) [201–204] and intramuscular (iEMG) [205, 206] electromyography, and electroencephalography (EEG) [207, 208];
3. methods which consider *physiological processes* inside the human body and their effects, for example electrodermal activity (EDA) [209–211], electrocardiography (ECG) [207, 212, 213], pupil size (PS) [214, 215], blood pressure (BP) [216, 217], heart rate (HR) [216–218], respiratory measurement (RM) [219–221], etc.

In contrast to questionnaires and observation-based methods, most of the direct measurement methods cannot be applied directly at a workplace, and necessitate special equipment and often also a laboratory set-



**Fig. 2.3:** Summary of direct measurement methods' informativeness vs. application complexity. Informativeness takes into account type of data, its detail and scope with respect to the whole human body. Application complexity takes into account complexity and time to set up a measurement system, complexity of individual subject preparations and level of expertise required from experimenters. The values were subjectively assessed through pairwise comparisons of each method's combination with respect to each variable.

Black—mechanical, dark gray—electrical and light gray—physiological methods.

ting. The complexity of experimental data collection depends on a particular method and can be relatively low for some methods and very high for the others, as we summarize in Figure 2.3. Multiple methods are also very invasive, which restricts possible application scenarios and could lead to unnatural behaviors during the experiment. We give more details on the most important methods and their applicability in the paragraphs below.

**The first category of methods** concern physical ergonomics most directly, as any mechanical activity or body movement is captured in this category. The mechanical methods can be split further into 3 categories, which complement each other in detailed analysis: kinematics, internal forces and external forces measurements.

Kinematics measurements include positions, velocities and accelerations of given points on the human body (CVMC, EMMC, IMUMC) or angular equivalents at given skeletal joints (MMC, EGM, CG, LMM), and is performed on a small segment of the body (EGM, CG, LMM) or on the whole body (CVMC, MMC, IMUMC). All measurements are non-invasive to the human body and some of them are also non-intrusive to a human activity, for example, as can be seen in Figure 2.4, CVMC necessitates only wearing a special skin-tight suit [222], or in the case of markerless motion capture, even specifies no other requirements besides keeping a line of sight between the user and cameras [223, 224]. Motion capture data is used for analyses of postures and human movement over the whole activity duration. All necessary analyses can be performed on it without manual frame-by-frame data inspection. For deeper insights about processes inside the human body, motion capture data can be used as an input to biomechanical simulation.

However, kinematics data alone does not provide any insights about actual muscle and skeleton tissue loads inside the human body, which are essential for ergonomics assessment. That is why it is usually complemented by external force measurement, and sometimes also internal force measurement. Internal muscle and skeleton tissue loads are defined by kinematics of movement considered in the context of inertial properties of the body, as well as external forces acting on the body, for example gravity, ground reaction force, chair reaction force, object weight and reaction force, etc. External forces are measured between contact points of the human body and the external world or object by introducing an intermediate force-sensing layer. For ground reaction forces this layer is represented by force plates or an instrumented treadmill; for other exter-



Fig. 2.4: Optical motion capture and external force recording during mid-air gestural interaction.

nal forces, specific force or pressure sensors are installed. In some studies external forces are considered as a stand-alone data source for ergonomics analysis, for example when looking at grasp force during mouse interaction [225], but more often they are considered jointly with motion capture data and in the context of biomechanical simulation.

In contrast to external forces, internal forces are much harder and more invasive to measure. Measurement of internal forces within an activity of interest is possible only by inserting special force transducers into corresponding tendons or muscles, and is not possible outside a clinical setting. Internal muscle forces are sometimes estimated in an additional experiment from measurements by isometric, isotonic and isokinetic dynamometers in order to tune muscle parameters in a musculoskeletal model. This allows more accurate simulation of an activity of interest.

In general, the group of mechanical process methods provide the best application complexity vs. informativeness trade-off for physical ergonomics assessment. As can be seen in Figure 2.3, most methods from this group (black abbreviations) are in left central and upper segments of the chart, which corresponds to low to average application complexity and average or higher informativeness.

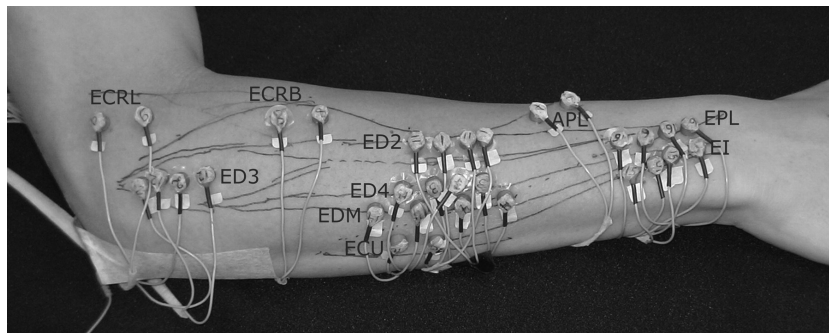


Fig. 2.5: Electrode setup for EMG of 10 forearm muscles [226].

The second category of methods describe electrical processes inside the human body. These processes belong to deeper levels in the system than mechanical processes and can be understood as control signals from the central nervous system (CNS) to the mechanical plant of the musculoskeletal system. The methods of this group consider electrical signals at each muscle (sEMG and iEMG), or more centrally, activations of various brain areas (EEG).

The human neural system transmits action potentials from the brain motor cortex to muscles similarly to electrical current. The action potential arrives to muscle at a motor end-plate, and then propagates along muscle fibers forcing them to contract and as a result generate mechanical force between opposite ends of fibers. EMG measures the difference in electrical potentials between two points along the muscle fiber located on the same side from the motor end-plate using either a pair of electrodes inserted into the muscle next to muscle fibers of interest (iEMG), or a pair of electrodes attached to the skin surface over the muscle of interest (sEMG). The force depends both on amplitude of the action potential and frequency, so there is a linear relationship between the linear envelope of EMG and force exerted by a muscle. To estimate muscle force from EMG an additional measurement is necessary: in parallel with EMG recording an isometric, isotonic or isokinetic dynamometer is applied during a similar type of muscle contraction. This makes it possible to approximate the relationship between the EMG envelope value and force output, and use the relationship further for estimation of force. A second additional measure of EMG is during maximum voluntary contraction (MVC), which is used as a basis for normalization between experiment sessions or participants. EMG can also be used to estimate fatigue, which is reflected in a frequency shift of the power spectrum.



While EMG methods are very informative, their complexity, limitations and invasiveness prevent wide adoption in ergonomics and HCI. They demand special expertise from the experimenters, in particular accurate muscle identification, and iEMG necessitates precise needle insertion. iEMG is very invasive and cannot be applied outside a clinical setting. Additionally, needles can cause discomfort in muscles during dynamic movements and prevent natural behavior. sEMG is not invasive, but it is limited to close-to-the-surface muscles, and is still intrusive to activities and naturalness of human behavior due to cables. sEMG data is also not very reliable, as it suffers from muscular cross-talk, or muscle drift during dynamic contractions. It contains a large amount of variability between participants and experiments due to natural day-to-day variation in skin conductivity. Simultaneous recording of a large number of muscles makes both surface and intramuscular EMG setup very cumbersome, complex, and time consuming, and impacts naturalness of movements; for example, Figure 2.5 displays the complexity of the setup for 10 muscles out of the 630 present in the human body.

EEG records electrical activity of the brain sensed by electrodes attached to the scalp. Unlike EMG, it cannot provide a fine-grained signal related to activation of a particular muscle, and gives only a high-level summary of brain area activity. In ergonomics it is used as an aggregated signal to detect general fatigue and sleepiness [207,208]. In HCI research it is used as an input method in brain-computer interfaces [227] rather than as an ergonomics measurement instrument.

**The third category of methods** considers physiological processes in the human body, such as heart rate, blood pressure, skin conductivity, pupil size, respiratory measurement and oxygen intake, etc. These processes reflect whole-body aggregated variables and are used for assessment of energy expenditure (RM in Figure 2.6), physical (RM, BP) or mental workload (PS), and emotions (HR, ECG, EDA), in particular stress (EDA). They require special equipment and can be applied in a laboratory setting, but they do not demand extensive specialized expertise from the experimenters. In HCI these methods can be used for general evaluation of an input method, but not for detailed analysis to inform design. With respect to informativeness these methods are better than questionnaires or observations as they provide objective quantitative data, but worse than other direct measurement methods as they do not provide enough details, despite having almost the same application complexity.



Fig. 2.6: Respiratory measurement of walking.<sup>2</sup>

### 2.3.2 Ergonomical Models

The methods described in the previous section provide a large amount of data describing human activity from a variety of possible perspectives, but to make sense of the data, mathematical and statistical models are applied, which aggregate the data and provide clear interpretable conclusions as output. A number of such models have been developed for physical ergonomics and human factors.

A large fraction of models directly correspond to and were developed in tight coupling with a specific data collection method; this especially concerns questionnaires and observation-based methods. For example, within REBA [170] the experimenter observes occurrence of events related to postures of six body segments and assigns corresponding ratings for each of them according to the scheme. Then the assigned ratings are

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used to compute two composite ratings for body posture (legs, trunk and neck) and arm posture (shoulder, elbow and wrist) using predefined tables. Further, the two composite ratings are combined into a single grand rating. The grand rating is then interpreted into severity of risks and priority of action on workplace improvement. Most other questionnaire- and observation-based methods use similar models, encoded as scoring tables (QEC, RULA) or as a linear formula (DMS, SI, OCRA Risk Index) for convenience.

More interesting and complex models were developed for direct measurement data. We have classified them into the 6 following groups, although the boundaries between them are not always sharp:

1. direct health risk estimation models;
2. exposure-effect models;
3. anthropometric posture prediction models;
4. posture-based skeletal load prediction models;
5. models which predict physiologic measures; and
6. models of muscular fatigue and recovery.

The first group, health risk estimation models, is the broadest, and similarly to the questionnaire- and observation-based models, these take into account all collected data and directly output health risks. These models provide either high-level generic results, for example the model of overexertion [228], or alternatively consider a small part of the human body and provide a more detailed result for it, for example a risk model of carpal tunnel syndrome [49, 229]. Such models were developed for assessment of lower back risks [230–234], neck and upper extremity risks [48, 63], arm and hand risks [235], carpal tunnel syndrome risks [49, 229], overexertion [228], etc. In most cases they are developed by a regression fit of a low-degree polynomial relating risk levels to a list of independent variables present in the data, which, besides other variables, usually includes force level and duration of the exertion. The drawback of such models is that they do not provide any information on internal loads imposing the risk, and in this way break the logical chain of load propagation, reduce interpretability and limit detailed analysis.

The second group of models generalize the models from the first group and describe the load propagation chain from external loads, through

internal loads, to acute and chronic effects. These models provide a conceptual framework for inclusive ergonomics risk assessment in the presence of data from various sources; in particular they make it possible to assess health risks not only from directly collected external load data for some body segment, but perform whole-body assessment based on internal physiological loads [236,237]. These models need physiological loads as input, so they can be applied only after the internal loads are measured or computed.

The third group of models estimate probable user postures for a variety of workplace setups [44,45,238], or physical properties of designed artifacts [239,240] based on anthropometric data of a user population. Unlike user studies, they can be used on early stages of design as inputs to the models which predict internal loads based on posture. The limitation of these models is that they provide predictions only for static postures. Synthesis of dynamic movements based on these models leads to unnatural movements transitioning between static postures.

The fourth group of models predict internal musculoskeletal loads based on measured user postures and external forces. These models use an inverse approach for computation of internal loads, in which they consider the whole kinematic chain, its inertial properties and applied external loads as inputs. The models belonging to this group range in complexity from simple link-segment models computing rough joint angles and moments in 2 dimensions [47,241–243] to high-fidelity full-body digital human models [46,47,244] able to compute joint angles, forces inside joints and moments at the joints. However, biomechanical models currently used in ergonomic computations do not predict muscular loads and activations by the neural system, which are important for ergonomics, energy expenditure and fatigue analysis. Often the models from this group together with anthropometric models are a core part of digital human simulations, described in Section 2.3.3.

The fifth group of models predict internal physiologic loads based on non-postural inputs. The most important and widely used inputs for physiological load estimation are EMG signals [245–248]. They enable computation of actual forces exerted by muscles and generated joint moments. Although these models can provide deep insights based on the physically measured data of muscle activity, they are also constrained by limitations inherent in both intramuscular and surface EMG data collection: low reliability for dynamic movements, limited number of accessible muscles or invasiveness, high between-session and between-subject

variability, high complexity and cost of experiments. Within this group there are also models which consider other types of inputs, for example the mass-spring-damper model of grip [249], pendulum model of walking [250], model of force distribution in the shoulder [251], etc., but they provide less accurate and insightful results than EMG-based models or the posture-based models from the fourth group.

The sixth group of models predict muscular fatigue, recovery and endurance during physical activity. They take as input the level of force exertion, its duration and repetitiveness, fraction of exerted force to the maximum voluntary contraction force, and sometimes also percentage of fast-twitch and slow-twitch muscle fibers, and compute the fatigue-recovery state of a muscle and its endurance in the context of a particular power output. Multiple models are developed within this group, for example the muscle fatigue-recovery model [252–254], work-rest model of discomfort and endurance [50], critical power and power-time to exhaustion model [51], etc. These models complement the models predicting internal physiological loads in the physical ergonomics assessment by quantifying the muscle state and potential work-recovery cycle and duration.

Often data collection and analyses in ergonomics are not limited to a single type of data or a particular model, and combine results of a combination of methods which support and complement each other. In particular this is common for modern ergonomics assessment software and digital human simulations [52,255,256].

### 2.3.3 Digital Human Simulation in Ergonomics and HCI

As mentioned in the previous section, digital human simulations are the closest ancestors of the biomechanical simulation within the fields of ergonomics and HCI. They are computer systems of complex models representing a variety of relationships within the human body and providing insightful outputs based on relatively simple inputs. The first digital human models were developed more than 3 decades ago to predict human reach and body size for automotive designs [257] using anthropometric data. Later more complex digital human simulations were developed which combined multiple models within one computer application and predicted potential postures and movements, their comfort, performance, a few types of internal physiological loads and ergonomics risks for the human body [52,53,255,258].

At the core of each digital human simulation are an anthropometric model which predicts body size proportions and a biomechanical model which predicts internal loads in various postures and movements. Current digital human simulations contain biomechanical models capable of predicting kinematics and dynamics, namely joint angles, joint moments and forces inside joints, but no movement actuation or muscles. Some of the models also try to predict human postures and movements, but the results lack smoothness and physiological compatibility [36, 259].

To our knowledge, biomechanical simulation *with muscles* has never been applied to HCI tasks. However, simple digital human simulations were integrated with motion capture in a few previous ergonomics tools, and applied to cases in office safety assessment [260] and automobile assembly analysis [256]. These implementations included simplified models without muscles which instead require additional EMG recordings [256].

### 2.3.4 Discussion

The field of ergonomics has a large number of sophisticated methods for physical ergonomics assessment in a workplace and in controlled experiments. Multiple types of data can be collected to describe the physical ergonomics, and multiple models can be used on top of the data to expand and interpret it. However, most data collection types are not suitable for design, and in particular for post-desktop input methods, either because of unreliability, or because of application limits, due to being too intrusive or needing too much expertise. Optical motion capture using a marker suit and external force recording provide the best trade-off between application complexity and information quality provided by the data. However, all models previously used in ergonomics can only poorly interpret the data.

Thus, in order to interpret the data in the context of the human body, we need to apply biomechanical simulation with muscles, which is new to the ergonomics field. Additionally, we can perform joint analysis of performance and ergonomics based on recorded data, which would provide even more benefits for the field.

## 2.4 Input Performance Assessment Methods

Input performance has been of major interest in HCI since the establishment of the field. There are multiple approaches to understanding input performance, its measurement and modeling. Most current input methods, except brain-computer and EMG-based interfaces, are based on human movements, for example moving a mouse, reaching to and pressing a key, selecting a target on a touchscreen, swiping a finger on a touchscreen gesture keyboard, or performing a mid-air gesture. The common performance measure for such movement-based input methods is speed and accuracy of the corresponding movements. Usually speed and accuracy are considered together in a trade-off relationship. This is reflected in a range of data collection methods and models for target-directed movements (Fitts' law [8], delta-lognormal law of kinematic theory [261]) and trajectory-tracking movements (steering law [262], sigma-lognormal law of kinematic theory [263]).

Data necessary for input performance analysis includes end-effector movement endpoints and durations, and for deeper analysis also movement time-histories and velocity profiles. It can be collected using a variety of devices, for example a pen, stylus, keyboard, mouse, joystick, light pen, touchpad, trackpoint, trackball, touch tablet, or touchscreen for 1D and 2D pointing tasks, and 3D mouse, motion tracking system, or computer vision system for 3D pointing tasks, etc. [8,112,261]

Fitts' law is the most widely used input performance model in HCI, which has already become standard for performance evaluation of input methods [95,264]. It was developed by Paul Fitts back in 1954 based on Shannon's theorem of information transfer [265], and expresses the relationships between movement time and task index of difficulty (ID) [41]:

$$ID = \log_2 \left( \frac{2A}{W} \right)$$

$$MT = a + b \times ID$$

Since that time tens of studies validated and used Fitts' law for analysis of aimed movements and movement performance prediction based on target size and movement amplitude. Multiple researchers proposed alternative formulations for the model [8,266], as well as new interpretations [8,261,267]. The most recent formulation of Fitts' law commonly used in HCI proposes to consider an effective target width instead of a fixed width

to better account for errors, and adjusts the index of difficulty to more closely reflect Shannon's theorem [95]:

$$W_e = 4.133 \times SD_x$$
$$ID = \log_2 \left( \frac{A}{W_e} + 1 \right)$$

Fitts' law was extended for 2-dimensional [268] and 3-dimensional [266] tasks by minor adaptations accounting for target width and height as well as for approach angle. A Fitts' law extension called the steering law is used for analysis of trajectory-tracking tasks [262]. It derives an index of difficulty for the whole trajectory by integration of the local amplitude to the tunnel width relationship over the whole length of the trajectory.

Despite the large number of user studies and wide range of applications, Fitts' law model and its direct extensions are still poorly backed up by the theory. Although it models well high level movement properties for large range of movements, it still fails for closer-to-boundary conditions, for example for low IDs the relationship is observed to be non-linear [269], or contribution of amplitude and target width are not equal, in particular for small targets [270]. While Fitts' law provides a relationship between aggregated movement properties and movement time, it lacks details on movement kinematics, in particular about trajectory and velocity profiles, which are important for complex trajectories or gestures.

As a result, significant effort was invested in physiologically-based models of movement and motor control, for example the VITE model [271] or kinematic theory [261]. These models use a notion of functional muscle synergies together with corresponding neural networks as basic subsystems for movement execution. These models provide good fit for the movement trajectories and velocity profiles and superior-to-Fitts'-law fit for the aggregated values. However, they still ignore complex skeletal chain kinematics of human movements. Considering biomechanics together with movement performance could provide new insights on human movement generation, and could potentially lead to refinements of the proposed models and theories.

### 2.4.1 Discussion

Input performance is one of the key factors in HCI and one of the most studied. A number of performance models are regularly used in research

and practice, most popular of which is Fitts' law. Although Fitts' law was extended for 2D and 3D tasks, it still does not consider multiple factors. First, it does not consider non-uniformity of the throughput with respect to location of start and target. Second, it does not consider movements with respect to the kinematic chain responsible for them, or the muscle groups which execute them. Third, it does not consider movement kinematics and dynamics beyond aggregated values of movement time with respect to target size and amplitude. Other models, although not as popular as Fitts' law, partially deal with one of the above mentioned aspects, though still not consistently. For example, kinematic theory considers dynamics and muscle groups, but it does not relate muscle groups to the physiology and kinematic chain.

The method we propose allows synchronous analysis of performance together with a particular movement, kinematic chain or muscle recruitment. This allows investigations of relationships between these factors, and could lead to improvement of current movement performance models by taking into account non-uniformity of space, or could contribute to development of new physiologically-based performance models.

## 2.5 Motion Capture-Based Biomechanical Simulation

Motion capture-based biomechanical simulation is an experimental and computational method developed in the field of biomechanics and adopted in the fields of medicine, rehabilitation and sports research. It "reverse engineers" observed motion to explain it in terms of anatomical events. Its input is the movement of pointlights in 3D space. When accompanied by information on how the pointlights map to the human anatomy (mapping and scaling), motion is first explained as rotations of joints (inverse kinematics). Then, given mass distribution of the body, required forces at joints are estimated (inverse dynamics). Finally, given muscle anatomy, plausible muscle activations are estimated (static optimization or computed muscle control). It makes it possible to precisely analyze natural human movements, and corresponding mechanical processes inside the human body, for example to assess movement deficiency sources, musculoskeletal risk factors and achievable performance improvements by athletes, or outcomes of potential surgery.



The method consists of a few important steps:

- Measurement of necessary musculoskeletal properties of a particular patient or athlete for adjusting the generalized musculoskeletal model to match his body;
- User study accurately recording the movement of interest of the participant with a motion capture system;
- Application of the biomechanical simulation pipeline to produce joint angles and moments, muscle forces, activations and excitations developed within the movement;
- Analysis of the simulation outputs, their comparison to “normal” ranges and patterns and identification of problematic spots.

The biomechanics community paid special attention to minimizing effects of measurement and modeling errors during all steps and developed corresponding practices and recommendations. We describe them and their possible application within HCI, while staying realistic about HCI goals, expertise, resources and experimental settings.

### 2.5.1 Optical Motion Capture

The key experimental input for biomechanical simulation and analysis is motion capture data describing human movements. This data consists of sequences of the 3D spatial coordinates of markers attached to human body or angular coordinates of joints within the body. It can be recorded by a variety of methods which can be grouped into 5 categories: marker-based computer vision (Vicon [272], OptiTrack [273], PhaseSpace [222], Qualisys [274], Metria Innovation [275]), markerless and depth-based computer vision (The Captury [276], Microsoft Kinect [277], Apple PrimeSense), electromagnetic (Polhemus [182]), mechanical (MetaMotion Gypsy [183]) and IMU-based (Xsens [278]) tracking.

Each of the motion capture categories has own advantages and limitations, which affect its applicability to biomechanical simulation, and within HCI. Mechanical and IMU systems are cheap and do not limit tracking volume, but they do not provide precision suitable for accurate biomechanical simulation. Additionally, they are cumbersome to apply and calibrate. Electromagnetic systems provide good precision and are applied in some cases for biomechanical simulation, but any conductors,



if present within the captured volume, distort the signal and recording, which significantly limits applicability for HCI tasks. Markerless computer vision and depth-based systems are the cheapest, easiest to apply and have great potential in future HCI applications, but at the current stage of development they provide limited accuracy, poorly suited for biomechanical simulation. The most widely adopted in conjunction with biomechanical simulation are the marker-based computer vision systems, as they provide sub-millimeter precision and reliable data. Their main limitation is that markers need to be within the field of view of the cameras to be tracked, which is usually considered when attaching the markers to a participant's body for a particular task.

In the last decade optical motion capture technology has not only matured, but also become significantly cheaper: for example, it is now possible to install a fully-functional optical motion capture system with a covered volume of  $3 \times 3 \times 2.5$  meters and with sub-millimeter precision of marker tracking for as low as \$20000 [21]. This allows wide adoption of motion capture systems and opens them up for more applications. In particular they are becoming more accessible for HCI laboratories, enabling biomechanical simulation for them.

The optical motion capture system consists of a few components:

- a set of high-speed cameras overseeing the capture space,
- a set of markers to attach to a captured person, or a suit with pre-attached set of markers,
- a camera synchronization and data processing system.

The cameras observe the space and synchronously record images of it. The markers either emit light of a specific frequency (active markers), or reflect infrared light emitted by lighting fixed to cameras (passive markers). As a result, marker locations on each image correspond to the brightest spots, so it is easy to identify them correctly and efficiently. The marker locations are then matched between the cameras, resulting in a reconstruction of their 3D position. The sequence of 3D positions of markers attached to all skeletal segments of the human body completely describes human movement [279].

Markers can be attached to the human body in various configurations, but they need to cover all skeletal segments of interest and conform to common practices or recommendations for optimal marker placement [279,280]. According to the recommendations, optimal accuracy can

be achieved by rigidly attaching at least 3 markers on visible locations of each skeletal segment, and additionally attaching 2 markers on two sides of each joint [280,281].

The accuracy of movement reconstruction is sensitive to errors within two mappings:

- mapping of all cameras to locations and orientations in 3D space, and
- mapping of markers to their locations in coordinate frames of corresponding skeletal segments.

Accordingly, two types of calibration are necessary before each session to reduce these errors:

- calibration of camera locations and orientations is performed by presenting a known pattern (checkerboard, system-specific “magic wand”) within the field of view of all cameras, covering as much of the field of view of each camera as possible. Additionally, a global reference frame is defined during this calibration step.
- calibration of marker locations with respect to reference frames of each body segment is performed by recording of a static posture, in which a subset of markers is attached to anatomical landmarks of a participant, while the rest of the markers are rigidly attached close to the middle of each skeletal segment.

In this thesis we analyze biomechanical simulation with optical motion capture data recorded in non-ideal conditions, with a non-optimal marker set, and with a reduced number of markers and spatial constraints on adjustment of each marker. Additionally, due to our HCI-specific physical setup, we deal with significant marker occlusions and reflections in the motion capture data.

### 2.5.2 Musculoskeletal Models

The core of biomechanical simulation is a model of the human musculoskeletal system. This model describes the human body as a mechanical multi-body system, which consists of passive elements constraining a movement (bones, joints) and active elements which generate forces and energy for movement (muscles) based on a particular control input

(neural signals). Mathematically this system can be interpreted as a set of non-linear differential equations. Biomechanical simulation fits this model to a user, then to motion capture data of particular movements, and outputs joint angles, then by deeper interpretation joint moments and forces, and finally muscle forces and activations.

Development of biomechanical models started from simple 1-joint kinematics models, adding inertial properties towards dynamic models and adding muscle properties towards musculoskeletal models. All simple models were developed using direct measurement experimental data from cadavers, X-rays, or joint moment or EMG measurements of living humans as can be seen in Table 2.1. The more complex models commonly integrate parameters of multiple simpler models, sometimes with adjustments if the source models are based on different types of subject populations (cadavers, students, adults, etc.), and compare the final high-level outputs with corresponding data. While these models can be considered as representing a “Frankenstein”, as different sets of parameters are collected from different populations, they still can provide realistic results, as discussed in Section 2.5.5.

The research effort in biomechanics community has been unevenly distributed between studying lower extremities, upper extremities and the trunk, resulting in uneven quality of full-body musculoskeletal models. While current lower-body models describe the human body in impressive detail, upper-extremity models are less developed, and trunk models are the weakest part.

The musculoskeletal models describe human body on 3 levels:

- **Kinematic** aspects describe rigid skeletal geometry, and osteo- or even arthrokinematics of joints between the rigid segments; in particular, high-fidelity musculoskeletal models can describe both complex joint-specific 3D translation and 3D rotation components of 1-DoF joint such as the knee, while low-fidelity models describe such a joint as a simple hinge with 1 axis of rotation. These aspects allow estimation of joint angles and the whole posture matching the motion capture data.
- **Dynamic** aspects describe inertial properties of each skeletal segment, like a mass and inertia matrix. Most biomechanical models describe each skeletal segment as completely rigid with constant inertia, while in real life soft tissues have a significant effect on resulting joint moments and forces and corresponding wobbling mass

models promise to reach more realism [282]. The dynamic aspects are necessary for estimation of joint moments for a particular kinematics.

- **Muscular** aspects describe active force generation within the human body by musculo-tendon units. The musculo-tendon units in musculoskeletal models are commonly represented by Hill-type models [283, 284] consisting of 3 components: active element, serial and parallel elastic elements. Such models are described by a force-length-velocity relationship (active), or tendon stiffness and force-length relationship (passive). Musculo-tendon unit implementations of current biomechanical models differ mostly in how the above mentioned relationships are numerically described, which directly affects feasibility, efficiency and accuracy of computations. Further, musculoskeletal models differ in the quality of muscle model parameters of each muscle: while in some cases the parameters are derived from cadavers, in other cases they are derived from healthy adults or sports students. The muscular aspects are necessary for estimation of muscle forces, muscle activations, and also excitations of muscles by neural signals.

In our work we use existing musculoskeletal models: the SIMM full-body model from MusculoGraphics [285] and the Upper Extremity model [286, 287]. They are state-of-the-art musculoskeletal models widely used in biomechanics, sports and rehabilitation research. We validate the outputs of these models against EMG measurements for HCI tasks, in particular full-arm mid-air aimed movements. Further, we use these models for analysis of various input methods, and as a method for gaining intermediate data for muscle co-activation clustering.

**Table 2.1:** Previous musculoskeletal models, their movement coverage and validity.

Model	Movements	Validated Body Parts	Type of Data	Drawbacks	Year	Reference
Lower Ex-tremity	Running	8 lower ex-tremity mus-cles	EMG, Pre-vious EMG	Completely dif-ferent part of body	2010	[288]
Index Finger and Thumb	Pinching, hy-pothetical rotation	Flexors and extensors of fingers	Pre-vious EMG	Different model and type of movements	1995	[289]

## 2.5. Motion Capture-Based Biomechanical Simulation

Wrist with 4 virtual muscles	Static poses	4 virtual muscles	Previous EMG	Simplified model, no movement, qualitative comparison to earlier data	1974	[290]
Elbow with 3 flexor muscles	Elbow flexion	Biceps, brachioradialis, brachialis	Validated predicted force	Simplified model, specific simplistic movement, only 3 validated muscles, no recorded EMG	1993	[291]
Elbow joint with flexor and extensor muscles	–	–	–	No validation	1996	[292]
Elbow with 8 muscles	Ballistic movements	8 muscles	EMG	Single joint, specific movements	1996	[293]
Elbow with 3 flexors	Elbow flexions with different speed	Biceps, brachialis and brachioradialis	Previous EMG	Simplified model, specific simplistic movements, lacks its own EMG	1997	[294]
Elbow with 8 muscles	Elbow flexion and supination	8 elbow muscle	EMG	Single joint, specific movements, qualitative comparison	1998	[295]
Elbow with 2 muscles	Elbow flexion	Flexor and extensor	EMG	Simplified model, single joint, specific movement	2000	[296]
Elbow with 5 muscles	–	–	–	No validation	2003	[297]
Elbow with 6 muscles	–	–	–	No validation	2005	[298]
Elbow with 5 muscles	Elbow flexions in horizontal plane	Biceps, triceps	EMG	Single joint, specific movements, only 2 muscles with EMG	2005	[299]

## Background & Related Work

Shoulder with 34 muscles	Arm elevation in sagittal plane	Anterior deltoid, supraspinatus, infraspinatus	EMG	Specific simplistic movement, only 3 validated muscles	1992 [251]
Finite element shoulder	Abductions of shoulder	12 muscles	EMG	Single joint model, specific simplistic movement in 1D	1994 [300]
Shoulder with 1 degree of freedom and two muscles	Goal directed shoulder movements in sagittal plane	Anterior deltoid and latissimus dorsi	Pre-vious EMG	Simplified model with no real muscles, simplistic movements in 1D of single joint, lack of correspondence between model muscles and muscles for which EMG was used	1994 [301]
Shoulder with 20 muscles	Aimed movement in sagittal plane	9 shoulder muscles	EMG timing	Single joint, simplistic movements, qualitative EMG timing comparison	1995 [302]
Shoulder with 30 muscles	Static posture	9 muscles	EMG	Single joint, static posture	1995 [303]
Shoulder with 30 muscles	Aimed movements in frontal plane	7 muscles	EMG	Single joint, small set of different movements	1995 [304]
Shoulder with 30 muscles for load-sharing	-	-	-	No validation	1996 [305]
Shoulder with 13 muscles	Wheelchair propulsion	13 shoulder muscles	Pre-vious forces	Single joint, specific movement, lack of own ground truth	2004 [306]

## 2.5. Motion Capture-Based Biomechanical Simulation

Upper Limb with 30 muscles	–	–	–	No validation	1992	[307]
Upper Limb with 21 muscle	Static pull	21 muscle of upper limb	Sum of forces	Static posture, no EMG	1999	[308]
Shoulder and elbow with 2 degrees of freedom and 6 muscles	–	–	–	No validation	2000	[309]
Shoulder and elbow with 6 virtual muscles	Constrained rotations	Posterior deltoid, pectoralis major, triceps lateral head, brachialis, long head of triceps, biceps	EMG	Simplified model, specific movements, lack of correspondence between model muscles and muscles with EMG	2004	[310]
Upper Extremity	Different static postures of the arm	Shoulder, elbow and wrist	Joint Moments	Static postures, no muscle validation	2005	[286]
Delft Shoulder and Elbow with 31 muscles	–	–	–	No validation	2005	[311]
Modified Upper Extremity	Specific reaching movement to single point in front	Anterior deltoid, biceps, triceps	EMG	Specific movement, only 3 muscles, qualitative comparison, lack of agreement between predicted activations and EMG	2009	[312]
Upper Extremity	Full-arm pointing in all directions and locations	8 upper extremity muscles	EMG, Previous EMG	–	–	This thesis [313]

### 2.5.3 Biomechanical Simulation

Biomechanical simulation is a set of algorithms which perform computations using a musculoskeletal model as a prior to fit motion capture and external force data, and output internal musculoskeletal model states describing joint angles and moments, muscle forces and activations for analyzed movement.

A musculoskeletal model is a complex mathematical system, which cannot be solved efficiently by current computing machinery when approached directly. However, efficient algorithms exist for subtasks, which can solve the biomechanical system in a sequence of consecutive passes. These steps correspond to different levels of musculoskeletal modeling aspects:

1. **Model Scaling** adjusts generic musculoskeletal model to match the anthropometric parameters of a particular person, namely the size of his skeletal segments, total body mass and mass distribution, and musculotendon properties. Scaling of individual segments is performed by either applying manual measurements of those segments—length, width, depth measured by measuring tape, or by applying automatic scaling ratios proportional to the relative distance ratio between a marker pair attached to the participants and a corresponding marker pair attached to the model. Mass for each segment is adjusted according to the same ratio, and further it is uniformly scaled to match the total mass of a person. Muscle fiber length and tendon slack length of musculotendon units are adjusted proportionally to the total musculotendon length. Usually markers used for scaling are placed according to anatomical landmarks close to opposite ends of a skeletal segment, which allows precise placement with respect to both the human body and the musculoskeletal model [17]. This step outputs a model which has proportions of the person, his weight, mass distribution and musculotendon parameters.
2. **Marker Adjustment** is performed after model scaling to improve spatial correspondence between the markers attached to a model and to a participant far from anatomical landmarks, usually close to the middle of a skeletal segment. While these markers exhibit the smallest soft tissue and skin drift during movements, advantageous for inverse kinematics, their precise placement on both partic-



ipant and model is very difficult. To improve the placement of the model markers with respect to the ones attached to a participant, modified inverse kinematics is performed on one averaged frame of static posture data with known minimal drift of the markers close to anatomical landmarks, which are considered by the algorithm as fixed, and shifting other markers locations to match their correspondences in the data [314]. After this step the markers on the model and markers on the participant are in close correspondence.

3. **Inverse Kinematics** fits the posture of musculoskeletal model to match the recorded motion capture data frame by frame. This algorithm corresponds to an optimization problem subject to kinematic constraints of the musculoskeletal model and minimizing an energy function of total squared error between virtual and physical markers and, if known, between the externally computed and the model's generalized coordinates, by adjusting the model's generalized coordinates as parameters:

$$\arg \min_q \left[ \sum_{i \in \text{markers}} w_i \left( \bar{x}_i^{\text{data}} - \bar{x}_i^{\text{model}}(q^{\text{model}}) \right)^2 + \sum_{j \in \text{coord.}} w_j \left( q_j^{\text{data}} - q_j^{\text{model}} \right)^2 \right]$$

where  $q$  denotes generalized coordinates,  $x$  marker 3D locations, and  $w_i$  and  $w_j$  weights of a particular marker or a particular joint coordinate. If the simulation inputs contain solely marker data, the second part of the energy function vanishes. This step outputs sequences of the model's generalized coordinates closely matching the motion capture data within each frame [17,314,315].

4. **Inverse Dynamics** computes total joint moments and forces emerging within movements described by the kinematics data. According to Newton's second law, point acceleration is directly proportional to sum of forces acting on it and inversely proportional to its mass, or equivalently:

$$\sum F = M \times a$$

Assuming that the human body consists of rigid segments of a particular mass and inertia, and measuring external forces acting on it, it is straightforward to apply the laws of classical mechanics, separate known forces and rearrange equation components to derive the forces and moments inside the human body:

$$\tau = M(q)\ddot{q} + C(q, \dot{q}) + G(q)$$

where  $q$ ,  $\dot{q}$  and  $\ddot{q} \in R^N$  are the vectors of generalized coordinates, their velocities and accelerations,  $M(q) \in R^{N \times N}$  is the skeleton's mass matrix,  $C(q, \dot{q}) \in R^N$  is a vector of the Coriolis and centrifugal forces,  $G(q) \in R^N$  is the gravity vector, and  $\tau \in R^N$  is the vector representing all generalized forces, namely total joint moments and total forces for translational joints [314]. All components on the right side of the equation are known from measurements or previous simulation steps, resulting in direct and straightforward computation. This step outputs joint moments and forces that need to be applied at each degree of freedom of the skeleton in each frame to produce the specified kinematics.

5. **Static Optimization** computes forces applied by each muscle and corresponding activations necessary to produce the total joint moments computed for each frame by inverse dynamics. It resolves muscle redundancy using an optimal force distribution assumption, namely that the human brain recruits muscles in an optimal way with respect to some objective function. Multiple objective functions have been studied in the past and optimality criteria were proposed, for example total muscle force, total squared muscle stress, total squared muscle activation, mechanically-based metabolic energy, biochemical muscle energy consumption, etc. [316–318]. It has been shown that squared muscle activation, while being a simple and computationally cheap objective function, provides a high correlation (0.85 in [318]) between predicted muscle cost and recorded metabolic cost ( $VO_2$  consumption); thus, it is the most widely used objective function in biomechanical simulation. The problem is formulated as a minimization of the objective function:

$$J = \sum_{m \in \text{muscles}} (a_m)^2$$

subject to a set of constraints describing the muscle force-length-velocity physiological relationship and relating muscle forces with total joint moments:

$$\sum_{m \in \text{muscles}} [a_m f(F_m^0, l_m, v_m)] r_{m,j} = \tau_j$$

where  $a_m$  is activation of a muscle,  $F_m^0$  is the muscle's maximum isometric force,  $l_m$  is the muscle's fiber length,  $v_m$  the muscle fiber

shortening velocity,  $f(F_m^0, l_m, v_m)$  the force-length-velocity surface of a muscle,  $r_{m,j}$  the moment arm of a muscle at a particular joint and  $\tau_j$  the total moment at the joint [314]. While static optimization performs computations frame-per-frame ignoring activation dynamics (activation value of each frame is not influenced by the values of preceding frames) and contraction dynamics (the tendon is considered as rigid and serial elastic element in muscles is ignored), it can produce remarkably similar muscle activations and joint reaction forces compared to the ones produced by computationally intensive dynamic simulation [319]. This step outputs muscle forces and activations necessary to produce the joint moments following the recorded kinematics.

6. **Computed Muscle Control** similarly to static optimization computes muscle forces, activations, and additionally muscle excitations by the neural system. Unlike static optimization, CMC performs more dynamically consistent simulation of movement taking into account contraction and activation dynamics, while still being computationally tractable, in contrast to full dynamic optimization. CMC integrates static optimization and forward simulation into a feedback loop with proportional-derivative control, as illustrated in Figure 2.7. In simple words, the muscle activations computed by static optimization are inputted into forward dynamics and integrated, then the difference between the resulting from forward dynamics kinematics and required kinematics are used to adjust the next static optimization input [17,320,321]. The outputs of the CMC algorithm are muscle forces, activations and neural excitations producing the given kinematics with the musculoskeletal model.

The described algorithms represent the state of the art in biomechanical simulation, and most of them or variations thereof are implemented in biomechanical software such as OpenSim [17], SIMM [322], AnyBody [323], LifeModeler [324] or SantosHuman [325]. Their effectiveness and efficiency has been shown in the biomechanics, rehabilitation and sports fields, but in this thesis biomechanical simulation is used for the first time in the field of human-computer interaction. In the HCI setting we shift the simulation application paradigm from application to a particular movement of a single subject in the context of a small body segment and tuning of hundreds of algorithm parameters, to a batch processing of experiment population data with a single set of algorithm parameters,

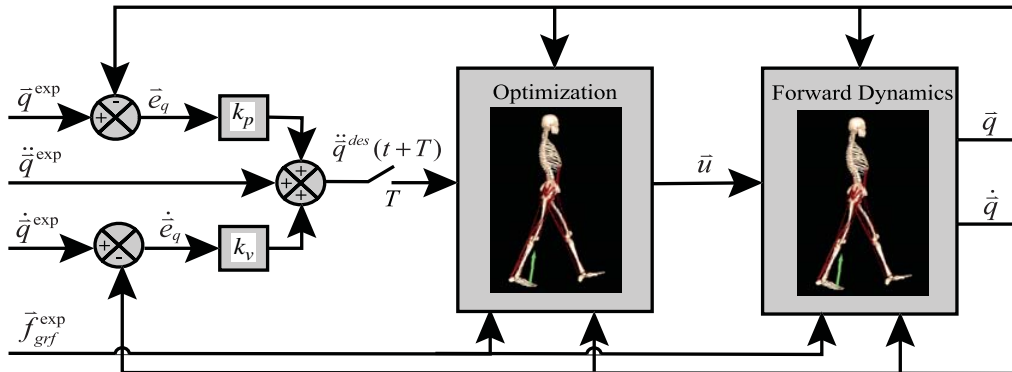


Fig. 2.7: Computed muscle control algorithm [321].

covering a large variety of movements and simulating the whole human body. We validate the produced simulation results against EMG recordings, and analyze the whole body results for different types of interaction using interactive visualization software and statistical methods. Further, we work towards simplification of the biomechanical algorithms, so that HCI researchers can run the simulations without tuning all the algorithm parameters.

### 2.5.4 Improvement over Traditional HCI Methods<sup>3</sup>

We here compare the outputs to existing measurements in physical ergonomics.

Motion capture and biomechanical simulation create a high-dimensional description of a user's movement. The output variables are best understood as descriptors of *physical ergonomics costs*, the anatomical and physiological costs of movement [326, 327]. Within this scope, mocap-based biomechanical simulation can estimate six out of eight measures that would normally require specialized measurement instruments (Table 2.2).

*Joint angles* are indicators of movement constraints and extreme postures and often measured by labor-intensive videometry, or goniometer measurement, which is limited to a few joints at a time and can perturb the movement. *Posture* is the state of the whole kinematic tree. It predicts overloading and musculoskeletal stress. In mocap-based biomechanical simulation, inverse kinematics yields angles and posture.

<sup>3</sup>This section is based on the paper *Is motion capture-based biomechanical simulation valid for HCI studies?: Study and implications* [313]

## 2.5. Motion Capture-Based Biomechanical Simulation

Instrument	Joint angles	Posture	Kinematics	Forces and moments at joints	Muscular load	Muscular activation	Fatigue	Experience
Goniometers	●	○	●	○	○	○	○	○
Videometry	●	●	●	○	○	○	○	○
Accelerometers	○	●	●	○	○	○	○	○
Force plates	○	○	●	●	○	○	○	○
Dynamometers	○	○	○	●	○	○	○	○
Surface EMG	○	○	○	○	●	●	●	○
Self-reports	○	○	○	○	○	○	●	●
DHM	●	●	●	●	○	○	●	○
Biom. simulation	●	●	●	●	●	●	○	○

● fully covered   ● partially covered   ○ not covered

**Table 2.2:** Comparison of biomechanical simulation against traditional instruments for physical ergonomics costs.

*Kinematics* describes angles and the distribution of loads and mass during movement and predicts overloading and repetitive-strain injuries. Force plates, on-limb accelerometers and on-joint friction/bending sensors can be used, but these have limited coverage, are cumbersome to apply, and can influence movements. *Moments and forces at joints* can estimate the overall energy expenditure [328] and also point to arthrokinetic strain and stress. Moments at joints are the sum of muscle forces multiplied by moment arms. Dynamometers are used in sports sciences but are limited to static setups and cover one movement type at a time. Mocap-based biomechanical simulation estimates moments and forces based on the outputs of inverse kinematics and full mass of the participant, assuming standard mass distribution.

*Muscular load* is the force produced by a muscle for a movement. Direct measurement of muscular forces is intrusive, but surface EMG [329] (sEMG) can be used to estimate it if parameters such as cross-sectional area are known. *Muscle activation* refers to the recruitment of muscle fibers by action potential induced by motor units. sEMG can be used for measurements, but it is limited to preselected muscles. In mocap-based biomechanical simulation, these two are given by static optimization.

*Fatigue* is the state of a muscle when it cannot produce its maximum force. It is reflected in the sEMG signal. Muscular fatigue can be described by total mechanical energy expenditure of a muscle, which can be calculated from muscle activations integrated over time, estimated by static optimization. Presently, the best way to measure muscular fatigue is to infer it from the EMG signal and to use self-reports.

*Self-reports* are verbal reports of effort, fatigue, and stress; they are typically measured via questionnaires administered after a task. A workload questionnaire widely used in HCI is NASA-TLX, which taps into some of these aspects. There are no published studies on the relationship between self-reports and outputs of biomechanical simulation.

### 2.5.5 Previous Validations of Musculoskeletal Models and the Simulation<sup>4</sup>

Although mocap-based biomechanical simulation has gained ground only recently, some steps of the simulation have been known for decades and are more thoroughly understood [327] than muscle activation models.

Error in joint angle prediction has been estimated to be within 1 degree for flexion–extension and abduction–adduction, and within 3 degrees for axial rotation [315]. Mean joint dislocations were smaller than 0.5cm, which should be accurate enough for HCI. Forces and moments have been validated in a study that compared the output of inverse dynamics to *joint moments* calculated with a machine learning algorithm from an EMG signal for the knee [328]. Model fit was high:  $R^2 = 0.91 \pm 0.04$ .

The only studies looking at the validity of muscle activation predictions of real movement of whole limbs involve lower extremities and consider gait or running [288, 330]. They compare predicted muscle activations against sEMG. Although there are few validation studies of simulations related to upper extremities, all of them are constrained and simulate only one-dimensional movements of a single joint. The previous validations of lower extremities or separate joints of upper extremities, as summarized in Table 2.1, do not generalize to the upper extremity model and cannot be considered as “valid” for HCI tasks [331]. The only study with a comprehensive upper extremity model reported, qualitatively, a lack of agreement in a comparison of predicted muscle activations and

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<sup>4</sup>This section is based on the paper *Is motion capture-based biomechanical simulation valid for HCI studies?: Study and implications* [313]

recorded EMG of 3 muscles for single specific reaching movement [312]. The validation study described in this thesis is the first exhaustive validation of upper extremity models for whole-arm aimed movements in all directions and locations.

### 2.5.6 Discussion

Motion capture-based biomechanical simulation is a powerful tool which allows to “look inside the human body”. However, there are still a lot of unanswered questions and potential for improvement of the method, in particular for the other fields which lack biomechanical expertise, or for other types of movements. Additionally, the method cannot be considered as valid by default for all tasks and movements. As already stated, the biomechanical simulation and models are much better developed for the lower body than for upper extremities and trunk, while for HCI upper extremities are of prime interest.

We contribute towards biomechanical simulation by simplifying application of the method for non-experts—we predefine most simulation parameters and then run the simulation for all trials and participants without fine-tuning. Second, we validate the predictions computed using the upper extremity model against EMG recording for whole-arm aimed movements of various accuracies, amplitudes and spatial characteristics. Third, we are the first to adopt and apply biomechanical simulation in the HCI field, as well as validate biomechanical simulation in the HCI setting with predefined parameters and an upper extremity model.

## 2.6 Summarization and Clustering of Physiological Data<sup>5</sup>

There is compelling evidence suggesting non-uniformity of human movement: two movements that differ in location, direction, and amplitude can and will vary in many important aspects, in particular in performance and ergonomics. Simplifying these heterogeneous patterns is one of the goals of our work.

First, *studies of movement trajectories* have shown the tangential velocity pattern generally to be asymmetric and bell-shaped [333]. However, sev-

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<sup>5</sup>This section is based on the paper *Informing the Design of Novel Input Methods with Muscle Coactivation Clustering* [332]



eral factors affect trajectory and velocity profiles, such as starting posture, the location of the end-effector, and ending posture [334], as well as the availability of visual feedback [335–337]. Movement properties also depend on ego-centric location and direction of movement [338–340]. Some of these effects have been captured in a number of movement models, including the minimum jerk principle [341], the torque change minimization model [342], and the endpoint variance minimization model [343]. Our experimental paradigm for data collection includes the effects of different starting postures, ego-centric location, and direction. No limitations were imposed on the use of visual feedback.

Second, *performance models* capture the speed-accuracy trade-off of pointing tasks (e.g., [261,266,343–345]). The earlier models treated movements as equal in regards to starting location and direction [8,41,268,346,347]. Some recent models have started to capture these factors (e.g., [261,266,348]). Because three target sizes were used and the whole 3D space of the arm covered, our dataset allows grouping any movements in the 3D space for performance modeling. The clusters we identify differ in movement location, direction, and amplitude. We show that performance prediction can be improved by segmenting the data based on muscle-based clusters.

Third, *studies of muscle dynamics* have shown a general three-phasic pattern of muscle activations from agonist to antagonist [349,350]. Muscle activations in the initial agonist activation are directly proportional to the duration of the acceleration phase [351,352]. Durations of the initial EMG bursts of the agonist muscles are proportional to the movement amplitude [350]. It has been found that the set of muscles activated at the initialization phase of movement depend on the target location [340]. Also, depending on the movement direction, a common waveform of muscle activation is scaled and delayed in a specific way for each muscle [353]. Furthermore, earlier studies have exposed codependencies, such that shoulder and elbow joints are coupled during movement, but the wrist is independent [354,355]. Our muscle activation data confirm the general pattern and as such, show large differences within the pointing space. The goal of our clustering is to capture the tendencies in the whole reachable space of the arm. As stated, no a-priori assumptions are made about muscle recruitment, but we identify classes in a data-driven approach.

We are aware of few attempts to apply statistical methods of modeling, classifying or clustering to biomechanical data. Santos et al. performed



clustering of kinetic and kinematic variables of gait, stair ascent and descent to identify different functional fitness levels of elderly people [356]. However, this work was focused on identification of the most relevant feature set, and used ground truth data identified in a separate test to assess quality of the clustering. Even fewer papers attempt to model and classify muscle activation patterns of arm movements. They are based on EMG recordings that were statistically related to kinematics or dynamics of the arm. [353] extracts two principal components from the EMG signals. These components contain similar patterns among muscles with the differences in amplitude and temporal shift, depending on the desired movement direction. Micera et al. [357,358] use machine learning techniques to classify EMG signals into three categories. The involved movements are all planar, and only three muscles are examined. These studies account for non-uniformity, but they cover only a narrow set of upper extremity muscles and are limited to close-to-the-surface muscles. Moreover, they do not associate the patterns to pointing performance.

### 2.6.1 Discussion

There is compelling evidence that human movements are non-uniform with respect to spatial location, orientation, amplitude speed and accuracy. However, there are not many attempts to tackle this non-uniformity with respect to ergonomics or performance. In our work we assume that the active components of the human body which produce movements are the muscles, and movements produced by similar muscle activations also exhibit similar properties. Thus, we compute uniform regions based on similarity in muscle activations. Our work takes the first step in the direction of non-uniform performance models—we identify smaller uniform regions within the non-uniform movement space reachable by the arm. Furthermore, based on those uniform regions, we provide a compact overview not only for performance, but also for ergonomics factors, as they are dependent on muscle recruitment.

## 2.7 Summary

We have described the state of the art of fields of HCI input method design, physical ergonomics, and biomechanical modeling and simulation in the aspects related to this thesis. Each field has own tasks, re-

search methods and models, but this work advances all fields by providing bridges between them and advancing each field by methods from the others.

The largest is the contribution to HCI input method design: we adapt and validate biomechanical simulation for HCI goals, tasks and settings, which makes feasible detailed analyses of gestural and mid-air interfaces to accelerate their development and wide adoption. We show the effectiveness of biomechanical simulation on analysis of touchscreen devices and the added knowledge compared to traditional methods. Our movement space summarization provides quick access to biomechanical properties of mid-air aimed movements based on movement location and orientation. The summarization can be used by input method designers without much prior knowledge in biomechanics, kinesiology or physiology, while knowledge of anatomy is still necessary to understand areas under load in the human body.

The contribution for the field of physical ergonomics is similar, but not as significant as for HCI, as ergonomists usually have better knowledge of human physiology and biomechanics, and while they were not able to perform such detailed analysis, the movement summarization may have less value for them.

The contribution to biomechanics is two-fold: we validate biomechanical simulation with an upper extremity model for new types of movement tasks and, by creating the simulation pipeline, we make biomechanical simulation more user-friendly and accessible to a wider range of users. In particular this aspect is important for doctors and practitioners who have knowledge of the human body, but lack technical knowledge to run biomechanical simulation, tune optimization parameters or adjust models.

# Chapter 3

## The HCI Biomechanics Pipeline

### 3.1 Introduction

Following the overview of modern ergonomics and biomechanics methods in the previous chapter, we answer **Research Question 1.1** in this chapter by adapting and framing the motion capture-based biomechanical simulation as a method suitable for the HCI field.

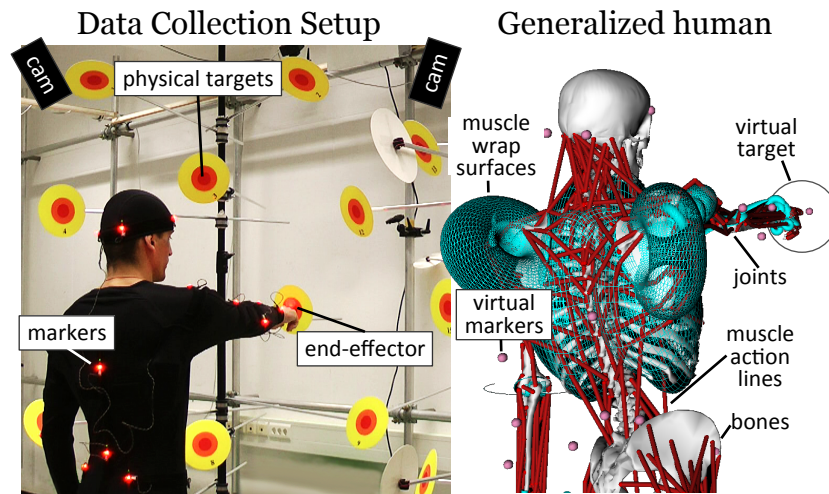
As already described, user performance and physical ergonomics are two key characteristics of input methods defined during the design process. A usable input method satisfies both these aspects by allowing high throughput (high words per minute for typing, fast target selection and menu navigation, etc.) and necessitating low ergonomics cost (postures closer to neutral, small joint and muscle loads, low energy expenditure and fatigue). For post-desktop input methods the problem of performance and ergonomics assessment becomes particularly hard due to such issues as lack of previous knowledge, large input space and its non-uniformity with respect to performance, and complexity of ergonomics analysis using traditional methods.

As presented in the overview of modern methods deployed in relevant fields, the most promising data collection method for our purposes is optical motion capture in combination with biomechanical simulation. While optical motion capture data is perfect for movement performance analysis (end-effector velocity, movement time, Fitts' law, throughput, etc.), it also serves as input to biomechanical simulation, which provides physical ergonomics variables for the corresponding movement. The computations are executed with a generic musculoskeletal model as a prior and generate joint angles, joint moments, muscle forces and activations.

The proposed analysis pipeline collecting and integrating both performance and ergonomics is shown in Figure 3.2. The pipeline is implemented in Matlab and includes the OpenSim biomechanical simulator [17] to generate biomechanical data. The experiments need to be performed in a motion capture laboratory and necessitate only slight adaptations to typical-for-HCI experimental setups and procedures. The preprocessing typical for motion capture data is applied to remove artifacts. This data is used further to derive performance characteristics, and in parallel it serves as the main input to biomechanical simulation. The resulting performance and ergonomics indices are synchronized and registered back in 3D movement space together with representation of experimental setup, namely the 3D targets.

The final dataset broadly covers both performance and ergonomics with more than 400 variables (for the upper extremity musculoskeletal model). Any movement can be analyzed and compared against others with respect to various types of indices, and at different levels of granularity, from frame level, to aggregates per movement and per movement type. In contrast to traditional methods, the richness of the dataset makes it possible to define the scope of the analysis a posteriori, rather than before the experiment. This gives the researcher additional advantages and flexibility in the search for general trends and anomalies. Another big advantage of the proposed method is the possibility of joint analysis of performance and ergonomics. This is the first method which tightly integrates both measures and makes it possible to systematically assess trade-offs between them, which would be very valuable for post-desktop interface designers and researchers.

Creation of the dataset is not the last step of the proposed analysis pipeline. To support the practitioners in analysis of such multidimensional multi-factor data we, together with our collaborators, have developed an interactive visualization tool. This tool makes it possible to explore different facets of the data using individual, most intuitive visualizations for them; for example, it supports 3D trajectory visualization to analyze end-effector kinematics; muscle visualizations to analyze recruitment, loads and energy expenditure; or task-specific visualizations relating indices of the data with spatial characteristics of the task. The tool supports joint analysis of the data across all three facets: performance, ergonomics, and task-specific movement characteristics; for example, it is possible to select desired movements in 3D space, then analyze their properties in ergonomics space (joint angles and moments,



**Fig. 3.1:** Terminology and setup for data collection. Markers on the human body are mapped via anatomical landmarks to a generalized model of the human. Physical targets are also registered in the virtual 3D space.

muscle forces and activations), or performance space (speed, accuracy, throughput). The tool is suitable for typical HCI decision-making tasks: validation, exploration and planning.

## 3.2 General Adaptation of the Method for HCI Studies

Previous industrial human factors work has developed mocap-based models of workers in reaching and assembly tasks (e.g., [359]). They simulate workers with different anatomical properties, but the models are highly task- and setup-specific. To be useful across the very diverse domains of HCI, mocap-based biomechanical simulation should not pre-specify a motion range. Moreover, a wide variety of movements must be covered in a single experiment.

Our goal has been to allow researchers to examine *any observed motion of the user* in 3D space for both *user performance* and *ergonomics*. Consequently we have identified the following subgoals:

- **Coverage:** Motions and aspects typical of HCI settings must be accommodated: 1) Contact with objects, which causes external forces; 2) multiple objects in the scene, causing occlusion of cameras; 3)

rapid, abrupt motions that can involve large forces; and 4) fine sub-centimeter movements such as those of the fingertips.

- **Efficiency:** The method has to allow efficient analysis of the whole population of potential users and consistently integrate them into a single analysis.
- **Simplicity:** The method must be streamlined to be applicable by researchers without specific expertise in biomechanics.
- **Motion segmentation:** Because performance indices require multiple observations, the whole motion sequences must be segmented into individual aimed movements.
- **Universal 3D registration:** Every trajectory must be augmented with both performance and ergonomics indices, and registered in a 3D coordinate system that includes 1) the user's virtual body and 2) input regions.
- **Multiple scales of analysis:** Output must allow analysis at the frame level (e.g., where the index finger is at a given moment), movement level (e.g., the trajectory for a multitouch rotation), and task level (e.g., what the average loading of the shoulder muscle is in a task).

### 3.3 Adaptation of Experimental Design

As shown in Figure 3.2, the first step of the proposed pipeline is to collect motion capture data in a user study. This data completely describes human movements recorded in the study, as well as the experimental setup. We list adaptations to typical HCI experiments necessary to apply the method.

First, the researcher defines the *movement space* for the study. Limitations are posed only by the optical tracking system. For the analysis of users' performance in *aimed movements*, which is typical for studies of input methods in HCI [95], it is necessary to set up the space such that the physical targets or input regions are observable by the cameras. For example, for the setup of Figure 3.1, the targets were instantiated by carton boards on aluminum sticks. If the space is in the ego-centric instead

Variable	Level	Unit	Count
<b>Physical space</b>			
Physical target 3D position	Trial	mm	3
Physical target size	Trial	mm	1
Effective target 3D position	Trial	mm	3
Effective target size	Trial	mm	1
Target amplitude	Trial	mm	1
Centroid amplitude	Trial	mm	1
End-effector 3D position	Frame	mm	3
<b>Performance</b>			
End-effector velocity	Frame	m/s	3
Velocity angles	Frame	m/s	2
End-effector absolute velocity	Frame	m/s	1
Mean movement velocity	Movement	m/s	1
Movement offset	Movement	mm	1
Index of difficulty	Trial	bit	1
Effective index of difficulty	Trial	bit	1
Movement time	Movement	ms	1
Mean movement time	Trial	ms	1
Throughput(4 types)	Trial	bits/s	4
<b>Ergonomics</b>			
Generalized coordinates	Frame	°	115
Moments at joints	Frame	$N \cdot m$	115
Integrated moments at joints	Movement	$N \cdot m \cdot s$	115
Forces inside joints	Frame	N	345
Forces exerted by muscles	Frame	N	351
Force integrated over movement	Movement	$N \cdot s$	351
Muscle activations	Frame	0-1	351
Activation summed over movement	Movement	0-1	351
Total muscle activations	Frame	0-1	1
-//- summed over movement	Frame	0-1	1

**Table 3.1:** Output variables produced by the method. *Count* is based on simulations with the SIMM full body model.

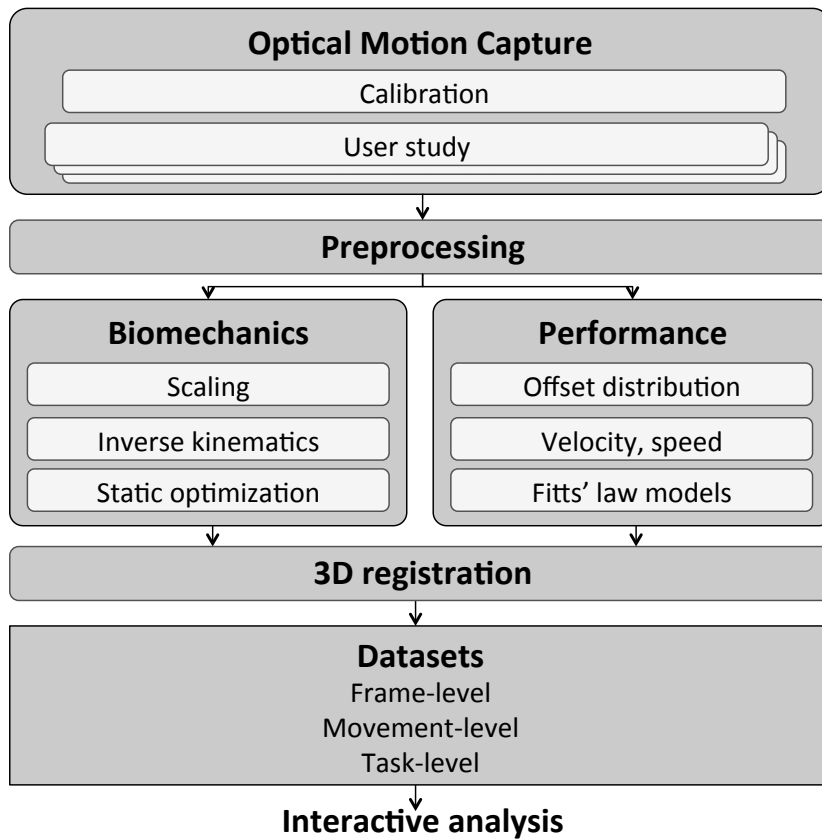


Fig. 3.2: Overview of steps required for use of biomechanical simulation in HCI studies.

of exo-centric reference system, the movement space must be *scaled* to the proportions of each subject. Linear geometric scaling can be used to adjust the target positions to the arm length and the height of a subject.

If *external forces* are involved—for example, ground reaction force if a user is jumping—or any other force is exerted on a physical object, *force sensors* should be used. We have used a Micro Load Cell (0–20 kg) with PhidgetBridge mounted under to-be-touched surfaces. For gait, force plates could be used.

For *marker placement*, we have followed recommendations for upper-extremity analyses based on *anatomical landmarks* [280] with some modifications due to limitations in suit marker placement. Our system (*Phase-Space* using *Impulse* cameras) tracks a full-body suit and gloves with flexibly attachable marker positions. For HCI cases, it is necessary to add further markers on the *end-effectors* (e.g., index finger). This minimizes the error in performance analysis.



For universal registration, two types of *calibration data* must be recorded prior to the experimental trials:

1. *Calibration for scaling to the user* involves 5–10 seconds recorded with the subject standing in a straight static pose with arms and legs extended (T-pose). This type of data is needed for *Scaling*. Alternatively, physical measurements can be used.
2. *Calibration for target registration* is necessary for physical targets. Calibration is done for each session and each user by touching the center of each target with an end-effector equipped with a marker. Such calibration needs to be performed for every session to avoid the effects of between-session changes in the coordinate system of the mocap equipment.

With these calibrations, a user study can be performed in an optical tracking system.

### 3.4 Data Preprocessing

The second step in the pipeline (Figure 3.2) is preprocessing of the collected marker data. The raw mocap data contains a number of artifacts caused by marker *occlusions*, *reflections* or *shifts in a set of cameras* observing a particular marker. The artifacts are typical when the user moves around or the scene is crowded. The first two issues manifest themselves as abrupt “jumps” in motion paths to that can be reliably identified from the second derivative of coordinate values that are further than 2 SD from the mean; the identified points are deleted from the data. The third issue can be identified as a shift of the whole sequence happening between two neighboring frames. In this case removing only the two frames does not help, and wider regions have to be cleared. After these two steps, the dataset has gaps that must be filled. We have experimented with several *interpolation* types and found linear interpolation to yield sufficient quality.

Finally, although most optical tracking systems can automatically smooth marker trajectories, additional *smoothing* is necessary for ID and SO. Any unsmoothed abrupt change in trajectory can only be explained in biomechanical simulation by an impossibly high use of force. We have tried standard methods, such as Butterworth, but found Kalman smoothing [360,361] to produce the best results.

### 3.5 Extraction of Performance Data<sup>1</sup>

After the data has been preprocessed, the pipeline (Figure 3.2) continues with extraction of movement performance data. For computation of performance indices, the whole mocap sequence must be first *segmented* into individual aimed movements. For reciprocal and cyclical aimed movements, we use local minima of absolute velocity of the end-effector marker, assuming that end-effector velocity falls to near zero in nearing the target and before the new movement begins. Given the calibration data, *movement time* and *velocity* can then be computed as indices of speed. *Offset* from the target center is derived as an index of accuracy. *Effective accuracy* is computed on the basis of a sphere covering 96% of movements that end within the target. Alternatively, the centroid of the effective target can be used for the cutoff. From the segmented data, individual movement *outliers* can also be easily removed via definition of cutoffs for speed/accuracy or distance to targets. From the segmented data, *indices of difficulty and Fitts'-law models* can be calculated for a given set of  $D$  and  $W$  parameters. We use a univariate model of pointing, but bivariate and trivariate models can be computed from this data (e.g., [266]).

We follow recommendations from previous research [95] and use the Shannon formulation of the index of difficulty (ID):

$$ID = \log_2 \left( \frac{D}{W} + 1 \right)$$

where  $D$  is the amplitude and  $W$  is the target width. The unit of  $ID$  is bits. We compute the *effective* target width  $W_e = 4.133\sigma$  and amplitude  $D_e = \sum_{i=1}^N D_i / N$  instead of  $D$  and  $W$ , where  $\sigma$  is the standard deviation of endpoint positions,  $D_i$  is the distance between start point and end point of a single movement and  $N$  is the number of aimed movements. We compute the coefficients  $a$  and  $b$  of Fitts' law using least squares fitting for a linear model:

$$MT = a + b \times ID_e$$

where  $MT$  is the average movement time. We assess the goodness of the fit by computing  $R^2$  for each model. Furthermore, we calculate through-

<sup>1</sup>This section is based on the paper *Performance and Ergonomics of Touch Surfaces: A Comparative Study Using Biomechanical Simulation* [118]

put  $TP$  for each condition as:

$$TP = \frac{1}{y} \sum_{i=1}^y \left( \frac{1}{x} \sum_{j=1}^x \frac{ID_{eij}}{MT_{ij}} \right)$$

where  $y$  is the number of subjects and  $x$  is the number of trials performed in a particular condition.

### 3.6 Extraction of Physical Ergonomics Data

After the preprocessing step (Figure 3.2), the conventional steps of the biomechanical simulation algorithm can already be carried out as described in Section 2.5.3. However, for computational reasons (biomechanical simulation is extremely time-consuming, in particular static optimization) we perform the simulation only on “representative” movement for a particular sequence of aimed movements. The “representative” movement can be identified as the one with performance properties closest to the average of the sequence. We use a single set of parameters tuned on example data to run the simulation for the whole dataset. As simulation in current software is implemented as single-threaded, we use external scripts to perform batch processing and parallelization of biomechanical simulation. For SO, additional reserve actuators can be added to ensure the existence of a solution, if the model contains too-weak muscles to explain abrupt or fast movements. The results should be checked for reserve activations, and if they are large, the virtual model should be better tuned to the individual subject [314].

### 3.7 Spatial Registrations of Data

After the extraction of performance and biomechanics indices, all 3D datasets are aligned and transformed in accordance with the calibration data (Figure 3.2). We compute the transformation between two target setups by optimizing least-squares errors between the references and post-transform positions. These transformations are further applied to 3D data of aimed movements and aligned in the same space, so that they can be jointly analyzed. If data are collected across multiple sessions, drift and shifts in the coordinate system of the motion capture tool must be addressed by the same method.

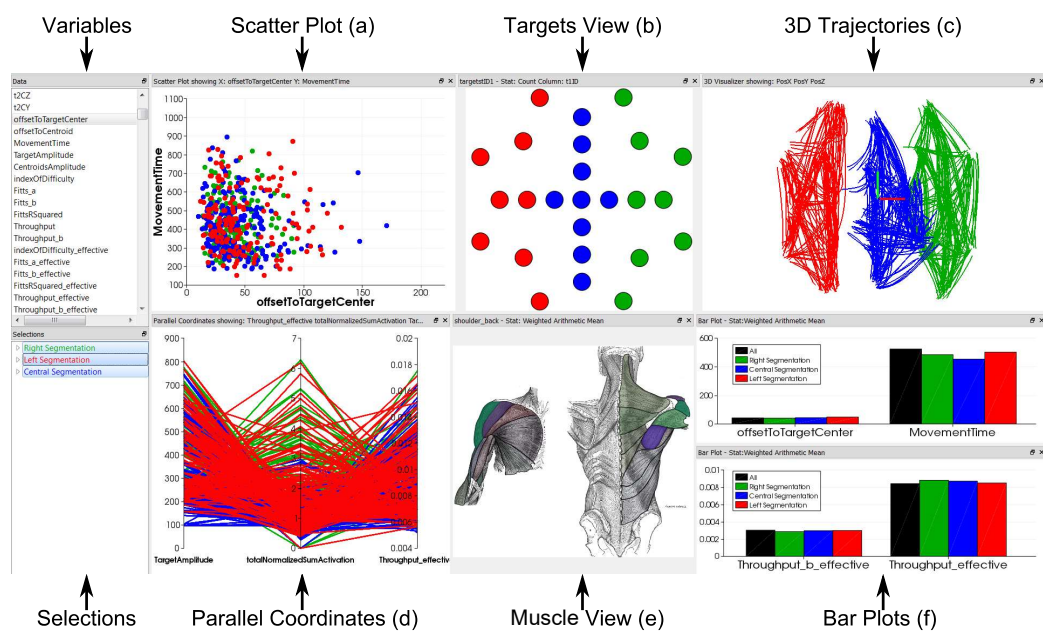
## 3.8 Data Representation on Multiple Aggregation Levels

The next step in the pipeline (Figure 3.2) after spatial registration combines all types of data within a single table. To provide more flexible analysis, the dataset is represented on multiple aggregation levels. The frame level corresponds to the data recorded by PhaseSpace Impulse motion capture system at 480Hz. The movement level corresponds to the spatial performance and ergonomics values aggregated for each individual movement. Aimed movement performance models are computed at the aggregation level per multiple movements relevant for particular targets. All values can be further aggregated with respect to a particular segmentation of the movement space (for example movements within 3 vertical segments: left, center and right) and finally the aggregated values for the whole movement space.

## 3.9 Interactive Analysis

The previous stages in the pipeline (Figure 3.2) produce a high-dimensional and complex dataset with hundreds or even thousands of variables describing complex interrelations between performance, postures, joint loads, muscle recruitment and energy expenditure, target locations and sizes, etc. For example the dataset created using the SIMM full body model contains 2125 variables (Table 3.1). Most of the variables describe physical ergonomics and can be related to a particular type of health risk: generalized coordinates (angles at joints), when close to joint limits, are related to increased risk of RSI; moments at joints can be related to acute injury when peak values are high, or to development of disease when integrated (accumulated) values are high; forces inside joints are relevant to risks of joint damage; peak forces exerted by muscles are related to acute muscle injuries; and muscle activations integrated over time correspond to energy expenditure and fatigue.

Evaluation and interpretation of such a large dataset becomes particularly hard without visual analysis, but available interactive visualization tools poorly support all facets of the data. As a result, we have worked on another step of the pipeline which supports such visual analysis. To achieve this, we have collaborated with experts in scientific visualization.



**Fig. 3.3:** Interactive analysis tool MovExp [362] with an application scenario.

The case describes a dataset of aimed movements between 25 targets covering the reachable space of the arm, namely within a half-sphere centered at the shoulder. To identify differences between movements in left, central and right parts of the space, we select corresponding three segments among targets in the setup (b). The 3D trajectories of corresponding movements can be observed and manipulated in 3D space visualization (d). Performance of the movements can be observed on the scatter plot (a) showing movement time with respect to accuracy. Further, the relationship between throughput, amplitude and total muscle activation can be investigated through the parallel coordinates plot (d). The muscle view (e) shows aggregated information on muscle recruitment during movements in corresponding space segments. Different types of aggregated values can be examined through bar plots (f). In this figure they show mean values for speed, accuracy and throughput.

We have specified the requirements for visual analysis software necessary to support HCI researchers and designers in evaluating datasets created by the proposed method. Further, our collaborators have created the interactive analysis software MovExp [362] (application example screenshot in Figure 3.3) which is able to handle such data, use intuitive spatial representations for all facets of the dataset, and flexible enough to accommodate task-specific analyses. Most case-studies in this thesis were analyzed using this tool and some of the corresponding visualizations are included in the thesis.

The tool provides common visualization functionality: scatterplots, histograms, parallel coordinates, 3D visualizations, barplots with inter-

active aggregation functionality, interactive linking and brushing [363] as a selection method and simple boolean algebra to combine selections. Besides this, the tool provides a muscle visualization method mapping muscle-related values to the opacity of corresponding polygon. The bases for all polygons are illustrations created by Henry Gray [364]. Additionally, the same technical structure can be used to create case-specific visualizations, highlighting for example target layout.

MovExp follows our goal to streamline the biomechanical analysis, and make it efficient and accessible to non-experts. The tool supports HCI practitioners in 3 scenarios:

- **Validation:** The data in the pipeline undergoes multiple processing steps, and to avoid artifacts, measurement errors, outliers or biases it should be visually assessed after each step.
- **Exploration:** Interactive exploration of the dataset is essential in identification of relationships, patterns, problematic spots, or good design trade-offs among performance, ergonomics and task variables.
- **Planning:** Practitioners can specify their design constraints in visual queries to identify the other facets of the hypothesized design. For example, they can specify performance, ergonomics and available task requirements and get a set of movements satisfying them as a result. Or inversely, they can specify a set of movements and get their performance and ergonomics characteristics.

### 3.10 Summary

We have described the integration of motion capture-based biomechanical simulation with movement performance analysis and task-specific variables into a single pipeline, whose outputs can be further effectively explored, evaluated and interpreted using the interactive visualization tool MovExp. This pipeline proposes slight adaptations to the HCI experiments, as well as to the common practices in optical motion capture and biomechanical simulation, resulting in an effective method for HCI researchers and designers. The efficiency and simplicity of the proposed method can significantly accelerate design of post-desktop input methods.

# Chapter 4

## Applicability of the Simulation for HCI Tasks<sup>1</sup>

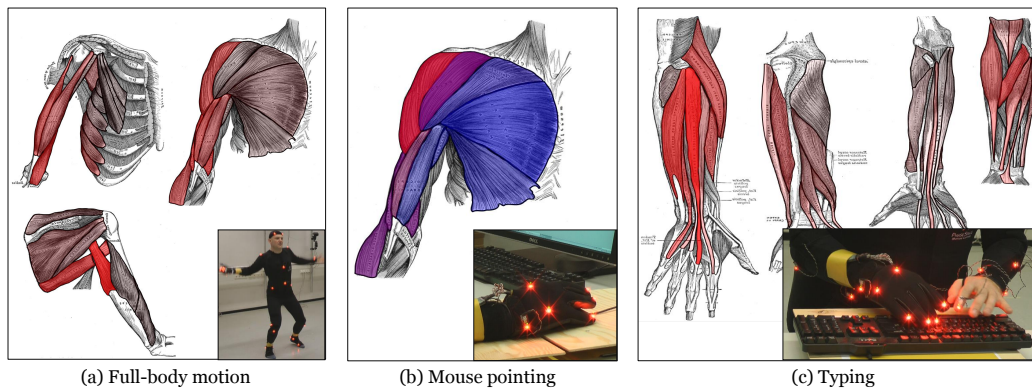
### 4.1 Introduction

This chapter describes the evaluation of technical feasibility of motion capture-based biomechanical simulation when applied to a range of HCI tasks. We respond to **Research Question 1.2** by performing a user study which covers HCI-specific types of movements with different spatial and temporal properties, as well as various body segments and muscle groups involved in the movement generation. First, a user performs a set of 5 tasks in a motion capture laboratory, and then we process the data through the biomechanical simulation pipeline and note if the computation fails. We consider the biomechanical pipeline as technically applicable for a task if all corresponding simulation steps succeed. Typical simulation error examples are discontinuities in IK output, muscle activations reaching the maximum boundary, or large activations of reserve actuators. Additionally, when available, we compare the simulation results against existing EMG measurements for similar tasks described in previous work.

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<sup>1</sup>This chapter is based on the paper *Is motion capture-based biomechanical simulation valid for HCI studies?: Study and implications* [313]





**Fig. 4.1:** Selected muscle activation predictions for three HCI tasks in the applicability study. (a) Arm and shoulder muscle activations when moving the arm up in a dance game. (b) Shoulder activations for mouse pointing: Activation marked in **blue** is for movement to left and **red** for right. (c) Muscle activations in hand and arm muscles for typing two letters with the middle finger.

## 4.2 General Setup

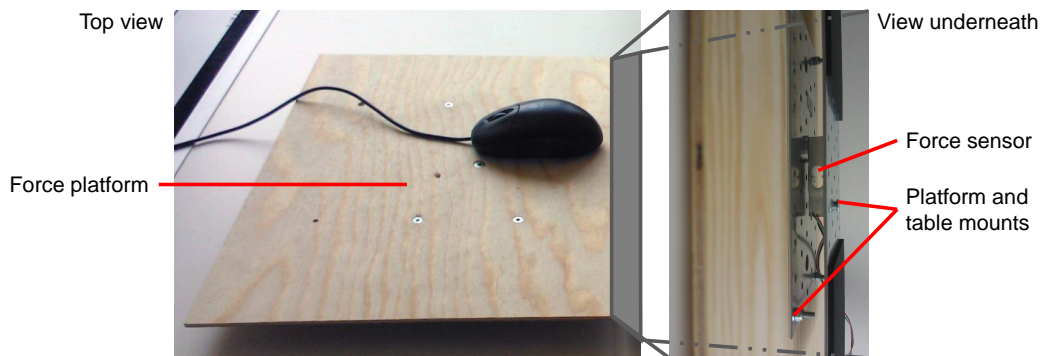
The current study examines HCI-relevant motor control tasks in 3D space. The system we utilize in the study represents the state of the art. Our recordings are done with high-end, commodity motion capture equipment: the *PhaseSpace* system with *Impulse* cameras tracks a full-body suit and gloves with flexibly attachable marker positions. For simulation, we use *OpenSim* [17], the only comprehensive open source simulator. It supports editing of the musculoskeletal model, scripting, and visual investigation of the results in a GUI. We use the SIMM full body model, which combines measurements from several anatomical studies [286] best representing an average adult male. It contains models of 118 bones, 86 joints, and 285 muscles.

In the user study we have followed the pipeline and adaptations described in the previous chapter, as well as the manual of *OpenSim* [314].

## 4.3 User Study

A 36-year-old subject (male, 178-cm, 78 kg) volunteered for the study. The subject is right-handed and has no perceptual, neurological, or cognitive deficits. As this study is focused only on *technical feasibility* of biomechanical simulation in application to various *HCI tasks*, there was no necessity





**Fig. 4.2:** Self-made force platform to measure main components of external force.

to recruit more participants. The *PhaseSpace* motion capture system with 12 Impulse cameras at 480 fps was used to record the movement of 43 active markers. In tasks 3, 4, and 5, a force plate of our own construction (Figure 4.2) measured the main components of external forces. Interactive software was used in tasks 1, 3, and 5. The tasks were performed in a single three-hour session. This allowed us to use a single calibration and scaling. Details of the tasks follow:

1. **Full-body dance game** involves configural movements of the full human body. It was performed to a song from *Just Dance 2* on the Nintendo Wii.
2. **Plane control** involves steering a plane through continuous aimed movements of the upper part of the human body. Three control schemes were used: The first used a “bird paradigm,” the second a steering-wheel paradigm. In the third, the arm was lowered and flexed. The subject had to mimic the motions of a person “flying” in a video as accurately as possible.
3. **Mouse pointing** involves fine-grained movements that deploy muscles from the shoulder down. It consisted of lateral reciprocal aiming movements performed with a commodity mouse. The control-to-display ratio was varied in three conditions: ratios of 4, 10, and 18 (scale: 1–20). Four target sizes and four distances were used, yielding 1280 selections in all.
4. **Multitouch gestures** on a surface involve fine-grained movements that employ the small muscles of the hand and the arm. We followed an existing gesture set [365]: rotation (45 deg, 90 deg, and

180 deg), pinch with two fingers (4 cm and 10 cm), pull with 2 fingers (4 cm and 10 cm), pinch with all fingers (10 cm), pull with all fingers (10 cm), drag with index finger (horizontal 4 cm and 10 cm, and vertical 4 cm and 10 cm), drag with four fingers (horizontal and vertical 10 cm), and tap with index finger. Each condition was repeated 50 times.

5. **Typing** involves fast simultaneous movements of multiple end-effectors and recruits small muscles. The participant typed his name as quickly and precisely as possible 50 times on a regular physical QWERTY keyboard.

In all tasks, the subject was trained prior to motion capture to reach a level of performance we considered representative for that task. Sufficient rest was provided throughout.

## 4.4 Analyses

We have processed the motion capture data through our custom Matlab scripts to clear it from marker occlusions and reflections, removed noise using a Kalman filter and then transformed it to a format supported by OpenSim. At the next stage we tried to process the data of each condition through the biomechanical simulation pipeline, trying to reach as far in the simulation steps as possible by adjusting the simulation parameters. We have documented the problems stopping progress in the simulation for the failed conditions. For the steps completed throughout the whole simulation pipeline, we have qualitatively compared the simulation outputs with the knowledge from previous literature.

## 4.5 Results

Table 4.1 summarizes the success or failure of the biomechanical computations for the specific HCI tasks. Three out of five tasks were completely successful. For these tasks, the method is discriminative and the outputs are sensible as highlighted in Figure 4.1 using representative muscle activation patterns. In particular, Figure 4.1a shows a clear activation of upper back, shoulder and biceps muscles when the dancer moves his arm up, and lower back, shoulder and triceps muscles when he moves his

Task	IK	ID	SO
Dance game	●	◐	◐
Flight	●	●	●
Mouse	●	●	●
Typing	◐	◐	◐
Multitouch gestures	○	○	○

● full success ◐ partial success ○ failure

**Table 4.1:** Completion of simulation steps for five HCI tasks in the applicability study. See text for details.

arm down. For the mouse pointing task (Figure 4.1b), different shoulder muscles (deltoideus anterior and pectoralis major vs. deltoideus posterior and medius) are activated for movements from left to right and vice versa. When typing (Figure 4.1c), the subject mainly used his middle finger, which is reflected in a higher proportion of activation of muscles controlling that finger.

To follow, we discuss our detailed observations during this study, in particular regarding the cases where the biomechanical simulation could not be applied (cf. Table 4.1):

### Inverse Kinematics

Data from all tasks except multitouch gestures could be processed for IK. IK requires keeping the RMS (root mean square) error within 2 cm and largest marker error less than 4 cm. Although such errors are considered to be normal for *full-body* simulation, they were too large for multitouch gestures where the movement size falls within this range. This resulted in fingers being “stuck” in the same pose during the simulation. The other borderline case is typing: in our particular case IK was successful, because the participant used only 3-4 fingers with pronounced up/down movements when typing. Had the participant used the ten finger touch-typing technique, IK would have failed.

### Inverse Dynamics

Tasks that are successful in the IK stage can proceed to ID. The only problem we encountered in this step were tasks where large external forces were applied. For dance, where the user jumped up and down, because we did not have force plates on the ground, we manually esti-

mated ground reaction forces based on observation of movements. This approach improved the validity of full-body results, but the results were not reliable for the lower extremities.

### Static Optimization

Our analysis here is limited to selected shorter segments ( $< 2,000$  ms) of the full recordings, because of computational intensiveness. Computing just 50 frames of SO for the dance task took 15 hours on a desktop computer with a state-of-the-art CPU, as, unfortunately, biomechanical algorithms implemented in OpenSim do not benefit from parallelization.

One observed limitation is due to movements that are produced by muscles that are stronger than the corresponding ones of the generalized model. Another was that of motions where limbs are *overextended* or produce very fast abrupt movements. A successful simulation of the “bird” controller in the flight task required adding reserve actuators at the shoulder joints. This issue can be partially addressed by adjusting the *muscle* parameters of the general full-body model to the individual participant. Similarly to ID, SO needs correct external forces, so only part of the outputs from dance can be considered valid.

### Agreement with literature

Muscle activation predictions of two cases—mouse pointing and typing—could be checked against an earlier report using EMG to compare the two input devices. Overall, muscle activation predictions agree with previous findings. While we cannot compare *absolute* values, relative activations agree: the trapezius descendens is 1.8 times more activated and deltoids are 1.3 times more activated when working with the mouse than when working with a keyboard [366].

## 4.6 Discussion

From the results we can conclude that the motion capture-based biomechanical simulation can be technically applied to a wide range of HCI tasks, and particularly post-desktop input methods with large whole limb movements, but there are a few factors influencing technical applicability of the method.

The first factor is the size of movements of interest considered in the context of the body part of interest. If we use the full-body model, the movements with amplitude shorter than 4 cm are not feasible, as the amplitude is at the level of the average full-body marker error, which allows the finger model to stay between the endpoints. This limits the method's applicability to such tasks as smartphone interaction, subtle button presses or finger manipulations. A potential solution could be to split the simulation into two parts: full-body simulation to get data for large movements and postural loads, and hand-only simulation to assess finger movements. For smaller musculoskeletal models, for example hand-only, the average marker error will be much smaller, which could allow the simulation of finger movements. Another solution is to either attach more markers to the hand and fingers [367], and increase the weight of these markers, or apply a markerless hand tracking algorithm [368] and apply the kinematics directly.

The second factor is movement range with respect to skeletal joint boundaries. If the recorded range is larger than those allowed in the musculoskeletal model of the average human, or close to the joint limit, the simulation produces incorrect results. This problem can be identified by examining IK results and fixed by additional model adjustment to a particular user, but this is a resource-intensive process.

The third factor is presence of external forces. Their inclusion observably improved realism of simulation even for small forces, as for example in the case of touch typing.

Most current limitations can be tackled by future research in biomechanics, improvements in the user interface of the biomechanical modeling and simulation software and development of cheaper force sensors. Such developments would significantly expand the application scenarios in HCI.



# Chapter 5

## Validity of the Simulation in the HCI Setting<sup>1</sup>

### 5.1 Introduction

This chapter considers **Research Question 1.3**; namely, it evaluates the validity of biomechanical simulation outputs against direct measures in a typical HCI task. A weak point of biomechanical simulation is the numerous sources of error, which can decrease reliability of the outputs. These sources of error come into play at each step, starting from marker placement and finishing with user-specific non-optimal muscle activation patterns. For successful biomechanical simulation we need to take care regarding these sources of error. Examples of fields where biomechanical simulation is successfully applied are medicine and sports. These fields have their own specific aspects, which tend to avoid or minimize the errors coming to the simulation from different sources. A goal of our work is to assess whether the simulation can be also successfully applied in HCI setting, which is quite different from medicine and sports. Here are the main contrasts between HCI versus medicine and sports:

- First, motion capture recordings and simulation in medicine and sports are performed by biomechanically educated professionals, who gather practical experience every day, while in HCI practitioners and researchers should not be obligated to have deep knowledge in biomechanics or physiology to use the simulation for interface design.

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<sup>1</sup>This chapter is based on the paper *Is motion capture-based biomechanical simulation valid for HCI studies?: Study and implications* [313]

- Second, that there are more resources in medicine and sports which can be spent to simulate the biomechanics of a single person. This allows spending more time on accurate marker placement and measurement of the person, taking additional measurements of muscle force, EMG, weight distribution, etc. and fine-tuning the biomechanical model to the person.
- Third, the goals of the simulation are different—in medicine and sports the goal is deep understanding of specific movements of the particular person, while in HCI our goal is to understand the whole movement space for a population of users.
- Fourth, in medicine and sports the simulation is initially focused on a specified body segment, which allows accelerating the analysis, while in HCI we need to look at the whole body and then identify possible ergonomics pitfalls.
- Fifth, medicine and sports are mostly focused on the lower extremities, gait and running, but for HCI the main interest is in the upper extremities and full-body movements, starting from small multitouch finger movements to full-body gestures.

Additionally, it has been found that current biomechanical models cannot be considered as “valid in general” and that they need to be validated for each type of task [331].

This chapter answers the question of whether motion capture-based biomechanical simulation is still valid in the HCI setting, considering the above-mentioned differences in typical applications of the method. We consider the biomechanical simulation as “valid” if simulation results are reasonably similar to the actual physiological measures. We choose muscle activations computed by static optimization and EMG for ground truth as measures for comparison for the following reasons:

- muscle activations are the values of interest for HCI, as they convey a measure not only for ergonomics risk, but also for muscular fatigue;
- muscle activations are the deepest simulation level, and thus they accumulate the largest errors; and



- the EMG is one of the few physiological measures we can directly compare to simulation outputs, for example joint moments cannot be easily measured in dynamic tasks.

To answer the question we perform a user study with 16 participants, recording both motion capture and EMG for a typical HCI task—aimed movements.

The study addresses the *predictive validity* of muscle activations in HCI-relevant motions. Informed by the applicability study (previous chapter), we decided to focus on gross movements instead of small ones, and chose mid-air pointing gestures as the topic. This topic is relevant for research on interfaces that use computer vision and accelerometers for control.

Surface-EMG was measured for eight muscles of sixteen subjects while performing a 3D pointing task. The participants carried out in-air reciprocal pointing movements among targets in the reachable space of their arms (Figure 5.1). The experimental design covered the whole reachable space of the arm and allowed us to vary target size and amplitude of movements. Moreover, we had 16 users with varying demographics, which allowed us to learn about potential inter-subject differences and differences between muscles.

EMG was chosen as “ground truth” following existing recommendations [331] in studies of lower limbs [288]. We use EMG amplitude as ground truth. This can be justified because for a particular muscle, larger EMG amplitude corresponds to larger muscle activation if 1) an EMG segment is recorded during con- or eccentric movement but not both, 2) cross-talk is minimized by precise electrode placement on larger muscles, 3) electrode displacement is minimal (here for 5 out of 8 muscles), 4) no between-muscle or between-movement comparison is carried out for EMG amplitudes, and 5) the absolute value of EMG is ignored (we use Pearson correlation as the metric).

## 5.2 Sources of Error in Biomechanical Simulation

To motivate the need for a validation study, here we outline the most significant sources of error in the method.

Generally speaking, the estimations of joint and muscle activities should be treated as *hypotheses* made possible by a strong prior: an anatomically

correct but generalized full-body model. The two most important sources of error are, first, the precision of motion capture that affects all computations “downstream.” State-of-the-art marker-based tracking is accurate to the millimeter level. For example, we used the *PhaseSpace* system in the studies, which allows 1/5 mm accuracy at 480 Hz. Second, every subsequent step in the simulation pipeline introduces unique sources of error, some of which are accentuated in HCI studies:

### 1. Marker Placement and Mapping

Biomechanical simulation depends on a reliable mapping between the body model and pointlights in the 3D mocap data. There are guidelines for marker placements that increase reliability by identifying *anatomical landmarks* that are more matchable (e.g., acromion, elbow) [280]. The mapping, called the *virtual marker set*, is manually defined after the data collection by the experimenter using a GUI.

*Sources of error:* First, typical optical tracking allows only a limited number of markers on the body (e.g., our system has 38). The experimenter must define which limbs to track and which to leave out. For example, tracking the articulation of hands is limited, if the rest of the upper torso should be tracked as well. Second, the placement of virtual markers on the model can never be perfect, since the virtual body model does not have the exact same geometry, and because markers are placed with an offset from the bones that mark the landmarks. Third, mapping is less accurate in segments that are farther away from anatomical landmarks.

### 2. Scaling

Every user needs to be scaled to match the anatomy of the generalized human model. A *measurement set* is a set of marker pairs and body parts that are scaled according to the ratio of distances between virtual and physical markers. The model size and weight are adjusted on the basis of the measurement set or from manual measurements. *Automatic marker adjustment* is then done based on data from a calibration pose of the user. It adjusts marker positions by means of inverse kinematics, which minimizes the errors between virtual and physical marker positions.

*Sources of error:* First, scaling assumes that the distribution of mass in a body is a linear function of the model’s distribution. Second, automatic marker adjustment can err due to improper weight distribution, causing correctly placed markers to be misplaced.

### 3. Inverse Kinematics (IK)

IK calculates generalized coordinates that describe a skeletal movement in terms of angles between bones at joints, and translations and rotations of the human model relative to the ground. It minimizes the weighted least-squares distance between physical markers and corresponding virtual markers.

*Sources of error:* First, markers can drift during movement due to non-rigid skin movement. Second, often for better computation speed, the joints are modeled as simple “hinges” and omit, for example, translation at joints [326].

### 4. Inverse Dynamics (ID)

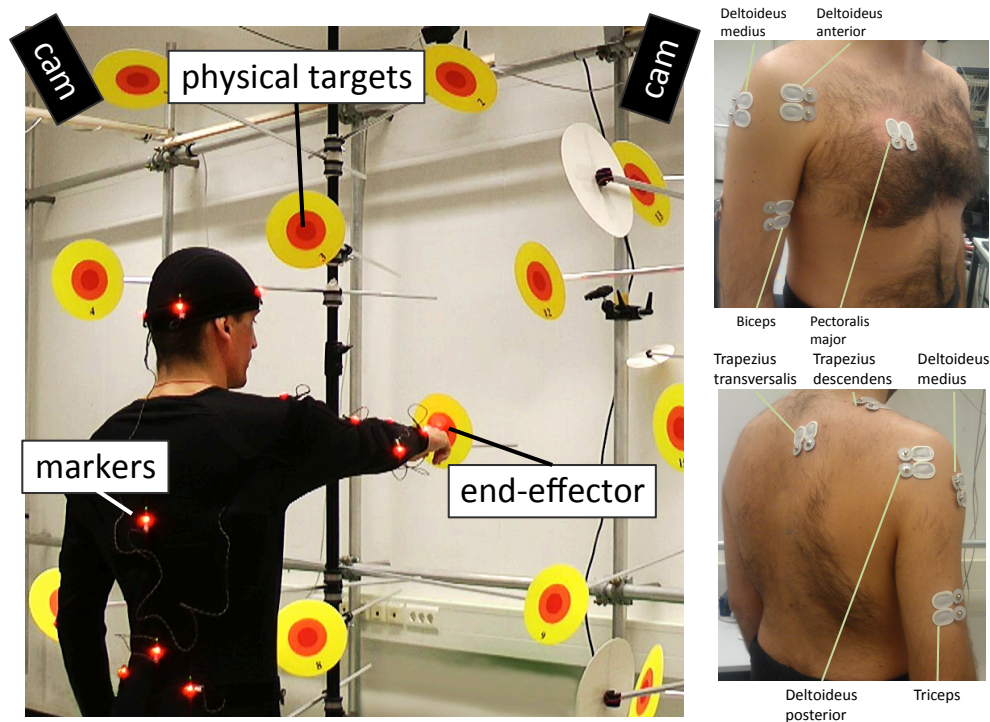
ID calculates forces and moments at joints produced by a movement given as a generalized-coordinate sequence. External forces can be added to the simulation at this step—for example, if they are recorded by a force plate, force transducers, or dynamometers.

*Sources of error:* First, measurements of external forces can be imprecise or temporally or spatially out of synch with the pointlights. Second, mass distribution and anatomy of a given user may differ from that of the model, causing inaccuracies.

### 5. Static Optimization (SO)

SO resolves the required activations of muscles by minimizing *total* muscle activation as its objective function. It uses two muscle models as constraints: ideal force generators and muscles constrained by force-length-velocity properties.

*Sources of error:* First, SO assumes that people move “optimally” in terms of minimizing total activation, which cannot be assumed in many HCI tasks. Second, muscle anatomy and strength may differ between the user and the model. Third, movement speed may be an issue: For slow movements, activation patterns could be identified incorrectly, because humans can use a different activation strategy, or use smaller musculature to move.



**Fig. 5.1:** *Left:* Experimental setup for the validation study: A 3D space with physical targets is scaled to the reachable area of a user’s arm. End effector and physical targets are tracked in addition to the pointlights of the motion tracking suit. *Right:* Electrode placement for the validation study.

### 5.3 User Study

Sixteen subjects (9 males and 7 females) with ages ranging from 21 to 36 ( $M = 25.9$ ), height from 162 to 178 cm ( $M = 170$ ), and weight from 61 to 79 kg ( $M = 70$ ) were recruited. No subject had musculoskeletal or neural disorders, and every subject took part in some regular physical exercise. While the recruited subjects group does not include extremes with respect to height, weight, age or physical condition, it covers a relatively wide population considering only automatic adjustment of the musculoskeletal model, which represents an average adult male. The population extremes, for example children, the elderly, or significantly overweight people, would need manual model adjustment or development of a new model to match the extreme in general before the automatic adjustment of the new model to a particular person.

Five targets from a total of 25 physical targets (see Figure 5.1) were selected for each subject by stratified sampling from five segments of the reachable space of the dominant arm: left upper outer, left lower outer, right upper outer, right lower outer, and central inner. There are three target sizes (20, 40, 80 mm). We recorded three trials for every pairwise combination of the five targets—in total, 30 trials per subject. The order of trials was randomized.

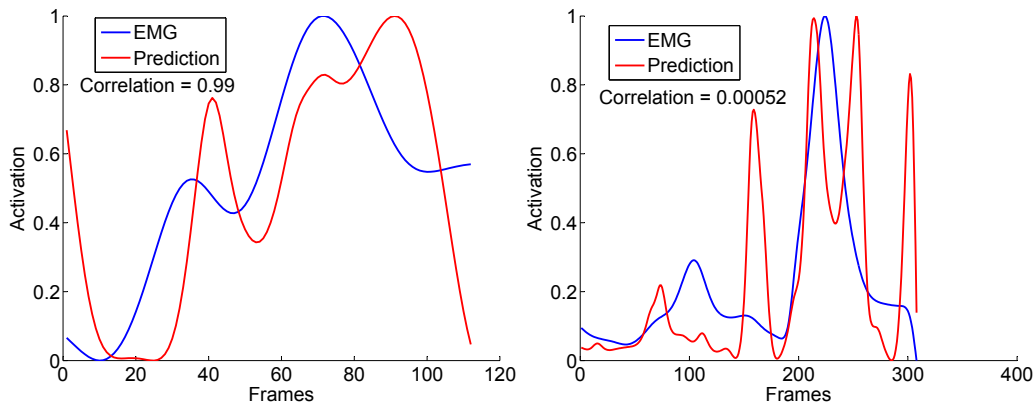
In addition to motion capture, surface EMG was recorded with a Myon 320 [369] and self-adhesive electrodes (Ambu Neuroline 720 00 S/25 with Ag/AgCl and conductive gel) at a sampling rate of 2000 Hz. All subjects confirmed that the EMG electrodes did not restrict their movements. Existing recommendations (SENIAM [370]) were used in electrode application to minimize errors from electrode-skin impedance, cross-talk and muscle drift. Electrodes were placed on eight muscles: the pectoralis major, deltoideus anterior, deltoideus medius, deltoideus posterior, trapezius descendens, trapezius transversalis, biceps, and triceps (see Figure 5.1). The skin was prepared for electrode placement following the same recommendations.

Retrospective self-reports were measured by a questionnaire. Subjects were asked to rate task difficulty and also the stress/tension in the muscles of the arm, shoulder, back, and chest with a seven-point Likert scale [371].

## 5.4 Preprocessing and Analyses

All motion capture data was processed through IK and SO. Because of the computational cost of SO, we selected representative movements by choosing a movement for each trial with a movement time closest to the mean and which ended within the effective target.

Following the recommendation of the manufacturer, the DC offset was removed from the EMG data and frequencies below 20 Hz, above 500 Hz, and between 49 and 51 Hz (power-line interference) were filtered. The signal was then full-wave rectified and normalized according to maximum voluntary contraction. Then both EMG and the activations calculated via static optimization were low-pass filtered at a frequency of 4 Hz to create a linear envelope of the signals.



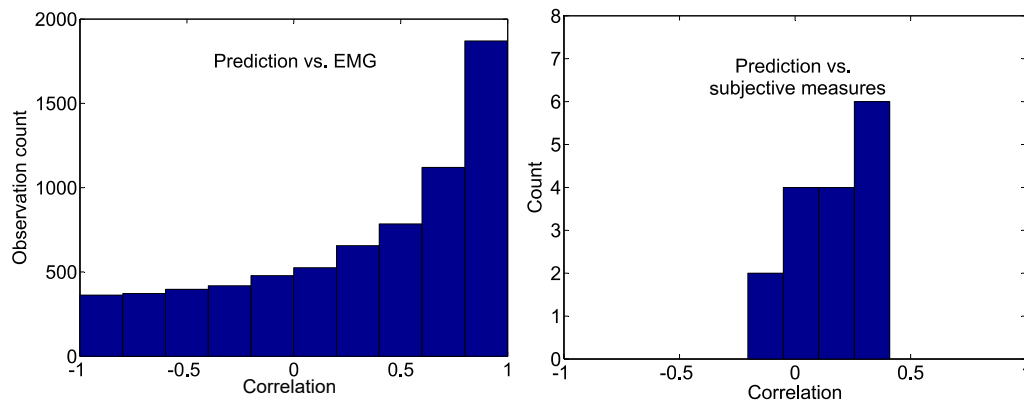
**Fig. 5.2:** Examples of EMG vs. predicted muscle activation with high (*left*) and low (*right*) correlations.

## 5.5 Results

For each movement ( $n = 960$ ), we computed the Pearson correlation coefficients between the time series of the EMG signals and the corresponding SO activations of the studied muscles. The full distribution of the correlation coefficients can be observed in Figure 5.3a. The median of the correlation coefficients over the full dataset is  $r = 0.48$ . Examples of high and low correlations are given in Figure 5.2.

We also segmented the distribution based on different independent variables (i.e. muscle, participant, target size or location) and analyzed distributions within segments. Several observations were made:

- SO predicts better for larger muscles: deltoideus ( $r = 0.64$ ) and trapezius ( $r = 0.67$ ). For smaller and less-recruited muscles, correlations are small or negligible: biceps ( $r = 0.27$ ), triceps ( $r = 0.04$ ), pectoralis major ( $r = 0.04$ ). This can also be explained by larger relative drift of the smaller muscles with respect to EMG electrodes.
- SO better predicts gross movements, i.e. movements toward *large targets* (8 cm radius;  $r = 0.59$ ) rather than small ones (2 cm radius;  $r = 0.37$ ). Perhaps the recruitment of smaller musculature in the finer control of motion is well captured by neither sEMG nor SO.
- Correlations differ significantly among subjects (range:  $0.33 < r < 0.62$ ), with the strongest correlations recorded for the oldest subject (36 years old, male). This is understandable given that the muscu-



**Fig. 5.3:** Distributions of correlation coefficients between predicted muscle activations and EMG (*left*) and between prediction and subjective measures (*right*)

lature in the model (SIMM-FBM) is based on measurements from adult males.

- Correlations increase in the course of a session (average slope=0.11%, in total 3.14% over 30 trials), perhaps because muscles are getting fatigued, so that muscle parameters of partially fatigued young people are closer to the muscles of an average adult in the body model.
- Self-reports of stress/tension have only a weak correlation ( $0.1 < r < 0.2$ ) with both recorded and simulated variables (Figure 5.3).

We did not find effects for the location of movement in the 3D space.

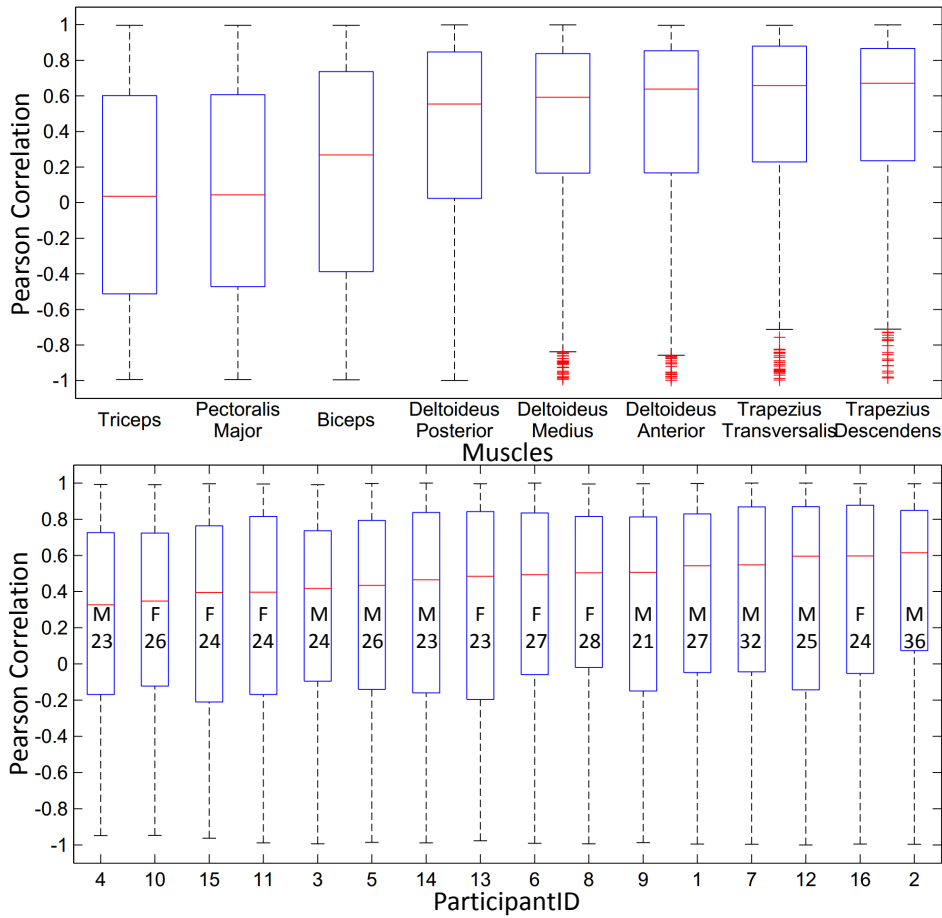
## 5.6 Discussion

From the results we can conclude that for HCI tasks the biomechanical simulation is valid and the outputs are similar to actual muscle activations in most cases. However, there are large variations with respect to muscle, subject and target size.

As we can see, all medians of Pearson correlations are positive, and for most muscles higher than 0.6, but for triceps, biceps and pectoralis major they are much lower. One possible explanation is that these three muscles were moving much more relative to the skin in contrast to the trapezius and deltoids, shifting muscle belly from under the EMG electrodes, which leads to an unreliable EMG measurement. However, as we do not have quantitative data to support this explanation, we cannot confirm that the



## Validity of the Simulation in the HCI Setting



**Fig. 5.4:** *Top:* Correlations of muscle activation predictions with EMG recordings. Break-down by muscle. *Bottom:* Breakdown by user.

simulation works well for small muscles. Thus, we would recommend focusing the experiments on large muscles.

The simulation produced valid results for all participants; namely, the median Pearson correlations are positive and larger than 0.3 for everyone. However, the variability is also present here: the median correlation is twice as high for a middle-aged male compared to a young female, which is understandable considering the model we used represents an average adult male. Our recommendation concerning participant selection is to select a wide population of participants, but in analysis of simulation outputs take into account lower prediction quality for participants different from the model.

Concerning the task, we see that predictions are better for larger targets. This can be explained by the higher speed of movements to large



<p><b>System Setup</b></p> <p>S1. Follow anatomical guidelines for marker placement.  S2. Use additional markers for end effectors.  S3. Use force plates to record contact forces at surfaces.</p>
<p><b>Data Preprocessing</b></p> <p>D1. Use reserve actuators for overextended movements.  D2. Use Kalman smoothing for more robust IK and ID.</p>
<p><b>Participants (based on the existing full-body models)</b></p> <p>P1. Middle-aged subjects are better predicted than young ones.  P2. Males are better predicted than females.</p>
<p><b>Tasks and Procedure</b></p> <p>M1. Movements with large amplitudes are better predicted.  M2. Movements to large targets are better predicted.  M3. Fine movements of less than 4 cm of amplitude are not feasible.  M4. Faster movements are better predicted than slow.  M5. Prediction is better for movements recruiting larger muscles.  M6. Prediction improves when the muscle gets more tired over time.  M7. Over-extended motions are poorly predicted.</p>

**Table 5.1:** Recommendations for improving accuracy of muscle activation prediction in HCI studies.

targets, which makes activations of the responsible muscles more prominent. Additionally, movements to large targets can be less accurate, so they need less co-activation of antagonists; as well, they can skip recruitment of small motor units with corresponding musculature. Thus, as a recommendation we note that the simulation results are better for faster and coarser movements than for slower and more accurate ones.

The self-reports were not predicted by the method, which needs further investigation.

To sum up, the biomechanical simulation at its current state already produces valid results for tasks in an HCI setting. While there is a lot of variation in output quality, for favorably chosen participants and subset of muscles, the median correlation is as high as 0.81. The summary of recommendations for new adopters of biomechanical simulation is in Table 5.1.



# Chapter 6

## Knowledge Added by Biomechanical Simulation in Input Method Design

This chapter addresses **Research Questions 2.1, 2.2 and 2.3** by applying the biomechanical pipeline to analysis of interaction with touch surfaces. It considers both performance and ergonomics as well as interaction between them in comparative study of 6 touch surfaces. Additionally, new ergonomic insights are described in detail for interaction with a tablet in a sitting posture.

### 6.1 Performance and Ergonomics of Touch Surfaces<sup>1</sup>

#### 6.1.1 Introduction

Nowadays people interact with multiple types of touch surfaces in everyday life. Half of the world population uses a smartphone as an everyday tool; tablets are less ubiquitous, but still widespread; laptops are increasingly getting touchscreens and becoming more similar to tablets; and interactive tabletops and public displays are gaining attention.

We analyze performance and ergonomics of interaction with the above-mentioned touch surface types. These factors were already studied be-

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<sup>1</sup>This section is based on the paper *Performance and Ergonomics of Touch Surfaces: A Comparative Study Using Biomechanical Simulation* [118]

fore, for example in [129, 133, 138, 141], but in most cases only a single surface type and single factor (either performance or ergonomics) was in the focus: tabletop [131], vertical display [130], tilted display [132], or mobile devices [133]. Each of the existing studies was also different with respect to task, performance or ergonomics measure, participant population, devices used, etc., which makes it impossible to compare results or consolidate them into a single body of knowledge. As a result, there is a lack of knowledge of how different form-factors affect touch interaction, which would be necessary to create applications compatible across devices.

In this section we describe a user study directly comparing the touch surfaces in a target selection task in a within-subject design. In this way we can directly compare performance and ergonomics factors among the surfaces. As a result, we can identify strengths and weaknesses of each surface type and trade-offs in speed, accuracy, joint and muscle loads and loads sustained over time causing muscular fatigue. From the findings it is possible to derive recommendations for design of user interfaces satisfying both performance and ergonomics requirements. In this way new designs can avoid or minimize adverse effects, for example “touch thumb”, “gorilla arm”, or “smartphone neck”.

While interaction with touch surfaces involves the same basic principle, namely “direct touch”, every surface involves different types of postures, limbs, movements and accuracies. We assume that these differences are reflected in the human musculoskeletal system, and the differences in performance and ergonomics characteristics of each surface can be attributed to the underlying biomechanics. Touch surfaces are very flexible in terms of how they can be situated in space. Furthermore, they can be carried on the user. This flexibility involves an immense space of possible interaction postures. In this study we do not limit the participants’ postures, allowing them to take whatever is preferred by them; based on this data we analyze the posture space and identify “typical” postures—the postures commonly used by participants. We analyze typical postures used in interaction with 5 surface types:

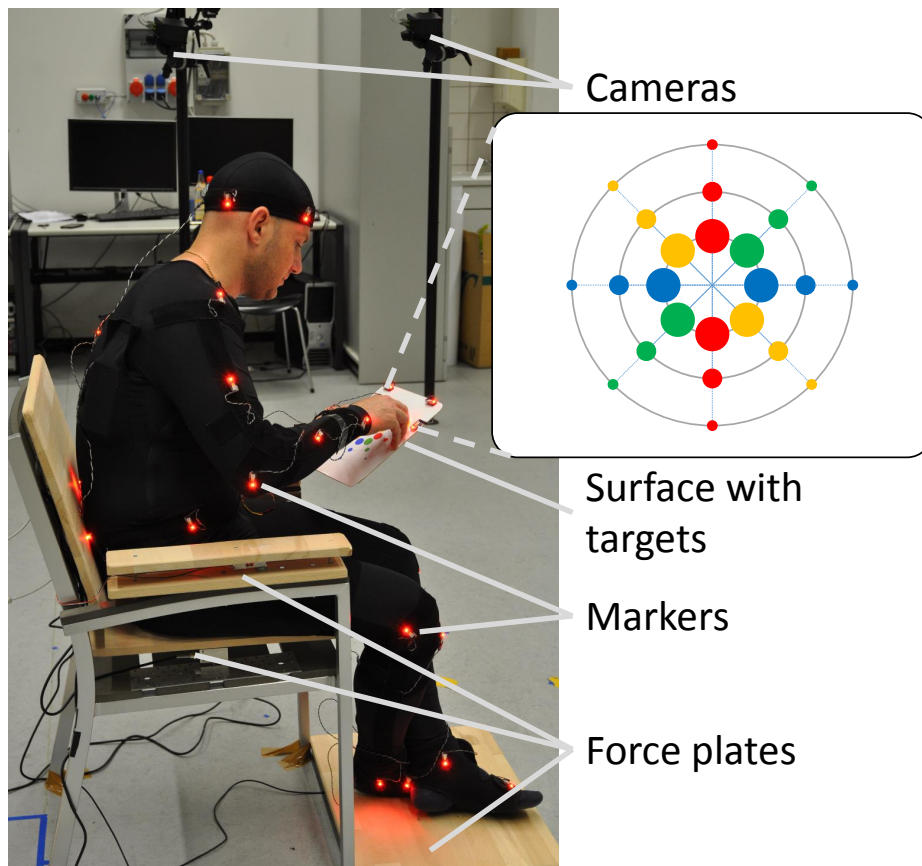
1. **public display**: large area, vertically positioned, used while standing
2. **tabletop**: large area, horizontally positioned, used when seated
3. **laptop**: medium area, adjustable tilted position, used when seated

4. **tablet**: medium area, handheld
5. **smartphone**: small area, used with one or two hands

In the user study we apply the motion capture-based biomechanical simulation pipeline described and validated in this thesis. Unique to this study is the free choice of posture by the participants for each touch surface. The time series of postures of all participants are then grouped per surface type and clustered into equivalence classes: similar postures used by different users belong to one class. Further, to attribute the performance and ergonomics characteristics to the posture type, more detailed analysis is performed individually for each class. In multiple conditions the users were interacting with the surfaces in a sitting posture. As mentioned in previous chapters, external force recording is necessary to make simulation in such cases more accurate; thus, we have instrumented a chair with multiple force sensors allowing measurement of main external forces.

While gesture-based input is becoming more popular, as an experimental task we have chosen aimed movements, as they are the most common type of input on touch surfaces, and in some cases even gesture-based tasks can be represented through a sequence of simple aimed movements. The task was a multidirectional Fitts pointing task, which is common for HCI experiments and allows computation of throughput (bits/s) based on speed and accuracy of corresponding aimed movements [95]. The target setup is equivalent with respect to indices of difficulty and directions for each surface, which allows direct comparison of performance between surfaces.

Additionally, we have consolidated the data into a single dataset, TOUCHCORPUS, and released it to the research community. This dataset includes the data from multiple processing levels of the pipeline: motion capture, speed, accuracy, throughput and measure of quality of Fitts' models, joint angles, joint moments, muscle forces and muscle activations. The dataset is generated on both the frame level as well as the aggregated per-trial level. We hope that this shared corpus will contribute to the replicability of user studies, and allow comparison of findings from studies of individual surfaces in a single context.



**Fig. 6.1:** The experiment was carried out in a motion capture laboratory equipped with a special chair instrumented with force plates. Surfaces were emulated with cardboard. The targets were registered in 3D space and tracked during performance. Here a user is performing the task in the Tablet condition (seated). The inset shows an example of the multi-directional target setups used in the experiment.

## 6.1.2 Experimental Method

This experiment compares six surface conditions in a multidimensional target selection task. All movements are recorded with a motion capture system. We built a chair with sensor plates to record external forces while seated. Figure 6.1 provides an overview of the setup.

### Participants

40 participants (26 males and 14 females) were recruited at the local university campus. The age range is 19 to 39 years, with a mean of 24.9. The range of heights is 156-190 cm (mean 171.4 cm). The range of weights is

47-95 kg (mean 67.4 kg). The right hand was the dominant hand for 38 of the subjects. No participant had a known musculoskeletal or neural disorder. We also collected their reports of previous experience with touch screens. Most participants used a smartphone on a daily basis. They were compensated for participation at a rate of 10 Euro/hour.

### Experimental Design

We follow a 6 x 12 within-subject design with 6 surface type conditions and 12 target selection conditions (see below). The order of surfaces was randomized for each subject, and within each surface condition the target selection conditions were also randomized. The surface types are: public display, tabletop, laptop, tablet, and smartphone with two hands or one hand. We have selected the most widely used condition for each surface type: standing for the public display, and seated in the other cases. The 12 target selection conditions consist of:

- **index of difficulty (3):** 2, 3.5 and 5 for small and medium surfaces; 2, 4 and 6 for large surfaces;
- **approach angle (4):** 0°, 45°, 90°, 135°

Target sizes on each surface were proportional to the screen size. They were 60, 28 and 10 mm for the public display; 50, 22 and 8 mm for the tabletop; 20, 14 and 7 mm for the laptop; 18, 10 and 7 mm for the tablet; and 7.5, 5 and 3.6 mm for the smartphone. Movement amplitudes on all surfaces matched screen size. In smartphone conditions amplitudes were shorter than marker error limits, limiting the applicability of the full-body simulation. Because biomechanical simulation has limited validity for small-scale movements [313], only 10 users participated in the two smartphone conditions in addition to the other ones. The remaining 30 participated in all other conditions except the smartphone conditions.

### Task and Materials

We used a multidirectional Fitts pointing task [95] with circular targets, 3 index of difficulty (ID) and 4 directionality conditions: in total, 12 conditions for each type of surface (the target setup is visualized in Figure 6.1). In contrast to a typical multidirectional pointing task in which users perform pointing movements, changing the target direction after each one, in our experiment the participant performed around 50 repetitive aimed

movements for each condition, without changing direction on the fly. The participant had to select the given target and then auditory feedback was given. Next, he needed to select the opposite target.

To minimize the effects of different surface frictions, sensor resolutions, accuracies and processing lags of various devices, we used target setups printed on paper and universal tracking with an optical motion capture system for all but smartphone conditions. The targets were printed on surface-size paper and affixed to a stand, a tabletop, and a tablet-shaped piece of plywood. The “tablet” is also tracked by the motion capture system through three rigidly attached markers. For the “smartphone” conditions we used a real device in addition to a motion tracking system, as we needed higher tracking accuracy at the targets than our motion capture system could provide. We selected the Galaxy S3 for this condition as a representative device, because its screen size is close to the market average, and it offers a screen with high performance and resolution. The target setup on the device was represented statically, similarly to the printed setups.

### Procedure

Each study began with the subject wearing the motion capture suit and standing in an upright static pose. This is necessary for musculoskeletal model scaling. Then the subject sought a comfortable posture for the surface we had selected randomly. The experimental task was then introduced and practiced. Next, the experimenter selected a random task condition and administered it with custom-written software. The participant first performed a calibration for two given targets by touching their centers, and the system stored the end-effector positions. We used this to provide auditory feedback while the task was performed.

Next, the participant could practice the task before the experimenter started the recording. The participants were instructed to perform repetitive aimed movements between a given pair of targets “as fast as possible while keeping the accuracy at a specified level”. The system counted 50 aimed movements and then gave the signal to stop the selections.

After the participant completed the task in all conditions of a surface type, a break was provided and the next device brought. Each session was split into 6 blocks corresponding to surface type, lasting approximately 15 minutes. The participants were allowed to take breaks when they wanted



to rest. After the trials, we conducted an informal interview. We asked about participants' experience with touchscreens and their preferred experimental condition, and we measured the weight of the participants.

### Apparatus

*Motion capture system:* The experiment was performed in a motion capture laboratory with no vocal or visual distractors during the tasks. Motions were tracked with a PhaseSpace Impulse optical motion capture system featuring 12 cameras. The system tracked 38 active markers attached to a skin-tight motion capture suit at defined anatomical points. We added extra markers to the end-effectors (relevant fingertips). The motion was tracked with a frame rate of 480 Hz and an accuracy of 1/2 mm.

*Chair:* External forces were recorded with a custom-built low-cost force chair and platform with two integrated Phidgets bridges and 8 load cells (2000N, 2x1000N, 5x500N; max error = 0.2%) (Figure 6.1). The chair sensed the most significant forces on the platform under the feet, under the seat, on the backrest and both arm rests and at two movable force platforms of 30cm x 40cm. The height of the seat was 50cm, width 45cm and depth 40cm; the height of the armrest was 70cm and width 8cm; and the backrest height was 95cm. The chair provided the force data at 125 frames per second. Figure 6.1 shows a user sitting on the chair in the Tablet condition.

*Synchronization:* Motion capture and force data were synchronized in real time using a custom-developed application on a high-end machine (Dell Precision M4800) to minimize latency (<5ms). For the smartphone conditions, we created an Android application for tracking touchscreen events. The touchscreen tracking had non-uniform sampling with an average framerate close to 60Hz.

### 6.1.3 Analyses

In our analyses we have followed the pipeline described in the Chapter 3 with slight additions to accommodate the tracking on smartphone touchscreen. The data from the smartphone touchscreen is aligned and synchronized with motion capture data during the preprocessing step; further, in performance extraction for the smartphone, the screen data is used directly. Besides the standard pipeline steps we add in this analysis a hierarchical clustering to identify common postures. This step is per-

formed after completion of biomechanical simulation and before dataset consolidation into a single table.

### Posture Clustering

During the trials, users were free to take any posture they wanted. To make sense of this data, we use hierarchical clustering on the inverse kinematics data to identify the main types of postures for each surface type.

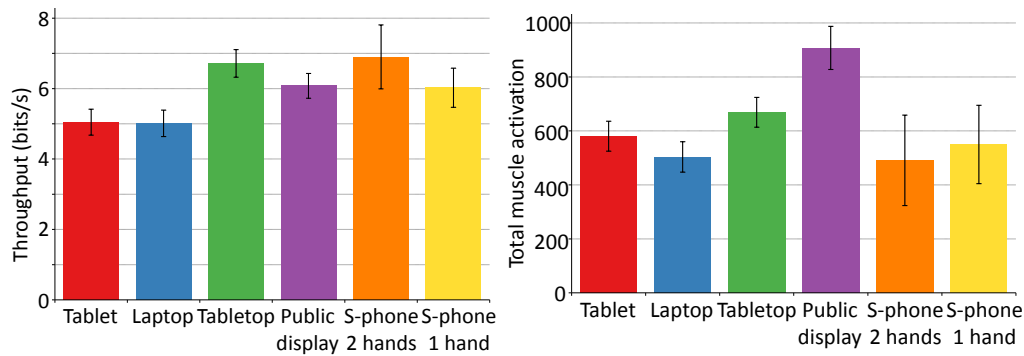
The inverse kinematics outputs serve as input for this step: the angles at joints calculated by inverse kinematics are applied to the musculoskeletal model of an average adult male, putting the model into the corresponding posture. In this posture we extract 3D locations of 22 keypoints at all joints of the human body and use them as input for the clustering algorithm. We have selected hierarchical clustering [372] because it is flexible and does not make assumptions about the data. We use Euclidean distance measure to treat all keypoints and dimensions equally. To acquire compact clusters with minimized variance we use Ward's linkage criteria.

To select the correct number of clusters we examine computed dendrograms and use multiple goodness-of-clustering indices: Pearson gamma, Dunn index, average silhouette width, and within-to-between ratio. The computations are performed in R with *hclust* from the *stats* package and *cluster.stats* from the *fpc* package. Following this approach, we obtained 7 clusters for the tablet, 3 for the laptop, 2 for the tabletop, 2 for the large display, 3 for the 2-handed smartphone, and 4 for the 1-handed smartphone. We introduce these postures later on in the paper.

#### 6.1.4 The TouchCorpus dataset

The outcome of these analyses is a dataset that integrates all variables extracted at different processing steps in a synchronized way. As can be seen in Table 6.1, the dataset includes 1181 variables describing different aspects of performance, ergonomics and experiment metadata. While the performance variables have been studied for years in HCI, the ergonomics variables from biomechanical simulation are more recent and therefore described here in more detail:

- *Joint angles* are related to the discomfort during the interaction. Operation of a joint at close-to-extreme angles causes postural discom-



**Fig. 6.2:** Throughput and total muscle activation per surface type. Vertical bars denote confidence intervals.

fort and poses high risk for future musculoskeletal disorder, for example repetitive strain injury or carpal tunnel syndrome. In the dataset we consider extreme values at all joints.

- Excessive *joint moments* cause high load on the joint tissues and can cause damage to the joint, in particular when high moments are sustained for a prolonged period of time. We consider peak moments as well as the values integrated over the whole movement.
- Large *muscle forces* stress the muscle and tendon and can cause damage to their tissue.
- *Muscle activations* take into account the muscle forces, but normalized by the muscle size. The activation value of each muscle ranges from 0 when the muscle is at rest to 1 when the muscle is maximally recruited. We use the muscle activations integrated over a whole movement as an index of muscular energy expenditure and fatigue.

### 6.1.5 Results

We used MATLAB, R and MovExp [362] for exploring the dataset. This section presents the main findings. We focus on basic indicators of performance (throughput) and ergonomics (muscle activation, muscle groups), and postures. For statistical testing, we use repeated measures ANOVA with an alpha-value of .05.

## Knowledge Added by Biomechanical Simulation in Input Method Design

Variable	Count	Aspect
Subject ID	1	Exp metadata
Device ID	1	Exp metadata
Trial ID	1	Exp metadata
Index of difficulty condition ID	1	Exp metadata
Approach angle ID	1	Exp metadata
Target ID	1	Exp metadata
Location of targets	6	Exp setup
Location of endpoint centroids	6	Performance
Offset to target center	1	Performance
Mean offset to centroid	1	Performance
Movement time	1	Performance
Target amplitude	1	Performance
Centroid amplitude	1	Performance
Index of difficulty	1	Performance
Index of difficulty effective	1	Performance
Fitts model parameters	2	Performance
Fitts model parameters effective	2	Performance
$R^2$ of Fitts models	2	Performance
Throughput	2	Performance
Throughput effective	2	Performance
Total mean muscle activation	1	Ergonomics
Total integrated muscle activation	1	Ergonomics
Extrema (min/max) of joint angles	218	Ergonomics
Peak joint moments	109	Ergonomics
Integrated joint moments	109	Ergonomics
Peak muscle forces	236	Ergonomics
Mean muscle activations	236	Ergonomics
Integrated muscle activations	236	Ergonomics
Posture cluster	1	Ergonomics

**Table 6.1:** Dataset variables extracted by the different types of analyses.

### Performance

We here focus on throughput as an aggregate metric of performance. Full data on speed and accuracy is provided in TOUCHCORPUS.

Figure 6.2 (left) provides an overview of throughput versus surface type. The effect of surface type on throughput was statistically significant ( $F_{5,8} = 9.24$ ,  $p < .0001$ ). It can be clearly seen in the figure that the tabletop has the highest throughput, and 2-hand smartphone follows in second place. The public display showed a slightly lower performance, while the laptop and tablet conditions saw the worst user performance.

## 6.1. Performance and Ergonomics of Touch Surfaces

Condition	Size	Support	Orientation	Color
Tablet	19 x 24.3 cm	Handheld	—	●
Laptop	31 x 23 cm	Supported	Tilted	●
Tabletop	110 x 70 cm	Supported	Horizontal	●
Public display	85 x 120 cm	Supported	Vertical	●
Smartphone 2-hands	6 x 10.6 cm	Handheld	—	●
Smartphone 1-hand	6 x 10.6 cm	Handheld	—	●

**Table 6.2:** The studied surface types. We introduce a color convention for the remaining analyses.

Average throughput was 6.55 bits/s. In the tabletop condition it was 20.5% higher than average. With the 2-hand smartphone it was 5.3% higher than average, and in the public display condition 5.2% higher. By contrast, with the 1-hand smartphone it was 8% lower than average, with the tablet 10.9% lower than average, and in the “laptop” condition 12.1% lower. Fitts’ law models elaborate this view.

Figure 6.3 shows Fitts’ law models for the six surface types. The plots show movement time ( $MT$ ) against index of difficulty ( $ID$ ). All Fitts’ law models had high fit, with  $R^2 > 0.95$  in most cases. However, there are some non-linear components visible for tablet, laptop, tabletop, and public display. Still, fitting a nonlinear model increased the fit by only 1-1.5%, and we therefore continued to use the linear model.

The Fitts’ law models elaborate the overview by crossovers. For example, there is a crossover for the 2-hand smartphone condition versus the tabletop condition. The tabletop is worse in low  $ID$  conditions. The plots also show that the 1-hand smartphone is different from other surface types, because it provides high performance that is pronounced in the low  $ID$  conditions. However, performance degrades much faster than in other conditions when  $ID$  increases.

### Total Muscle Activation

The effect of surface type on total muscle activation was statistically significant ( $F_{5,8} = 10.59, p < .0001$ ). Figure 6.2 (right) provides an overview.

We report standardized effect sizes for total muscle activation, as its units are coupled with our musculoskeletal model. We learn that total muscle activation was lowest in the laptop and 2-hand smartphone conditions. In the tablet condition, it was slightly lower than average

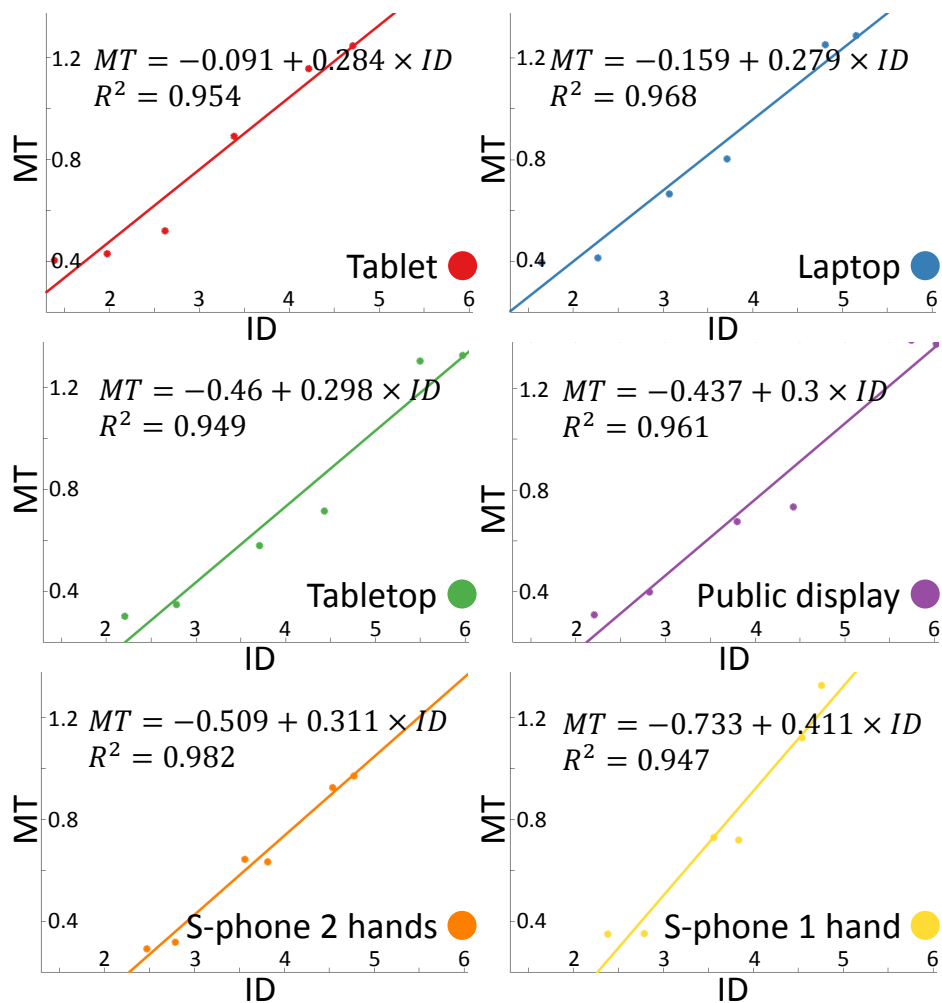


Fig. 6.3: Fitts' law models for each surface type.

("touchscreen in general"). It was the highest for the public display. The mean of total muscle activation was 608.1. For 2-hand smartphone use it was 19.2% better than average, for the laptop 18.6% better, for the 1-hand smartphone 9.6% better, and for the tablet 6.9% better than average. By contrast, the tabletop was 9.3% worse and the public display 45% worse than average.

### Trade-offs: Muscle Activation vs. Performance

We found a non-trivial relationship between (effective) throughput and total muscle activation, as illustrated in Figure 6.4. The figure shows second order polynomials fitted to the original data. The most surprising

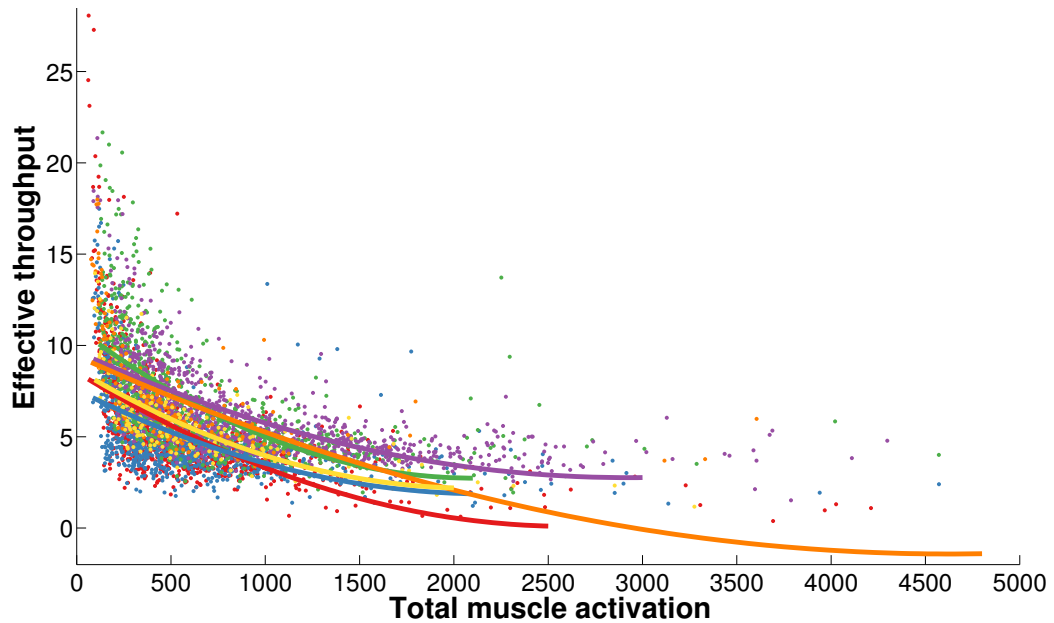


Fig. 6.4: Total integrated muscle activation vs. effective throughput.

pattern in the plot is that *low* throughput movements are associated with high muscle activations. The reason is that the lowest throughputs come from conditions with difficult-to-reach targets that require more careful control of muscles.

We also found that the approach angle influences throughput. However, it has no effect on total muscle activation. As stated before, average throughput is 8.5 bits/s. When considering the different movement directions, the highest throughput was found for horizontal movements (+9%) and the lowest for movements on a diagonal with 45° negative slope (-6%) and vertical movements (-5%). Movements on the diagonal with 45° positive slope have throughput close to the average.

### Muscle Groups

Although input with all surfaces is carried out with the same arm, biomechanical simulation exposes large differences in which muscle groups are involved.

Interaction with a tablet is characterized by high activations of side and back deltoids for the interacting arm. For the arm that holds the surface, we see higher activation in frontal deltoid, triceps, and infraspinatus. Laptop use is characterized by high activations of the front and medial



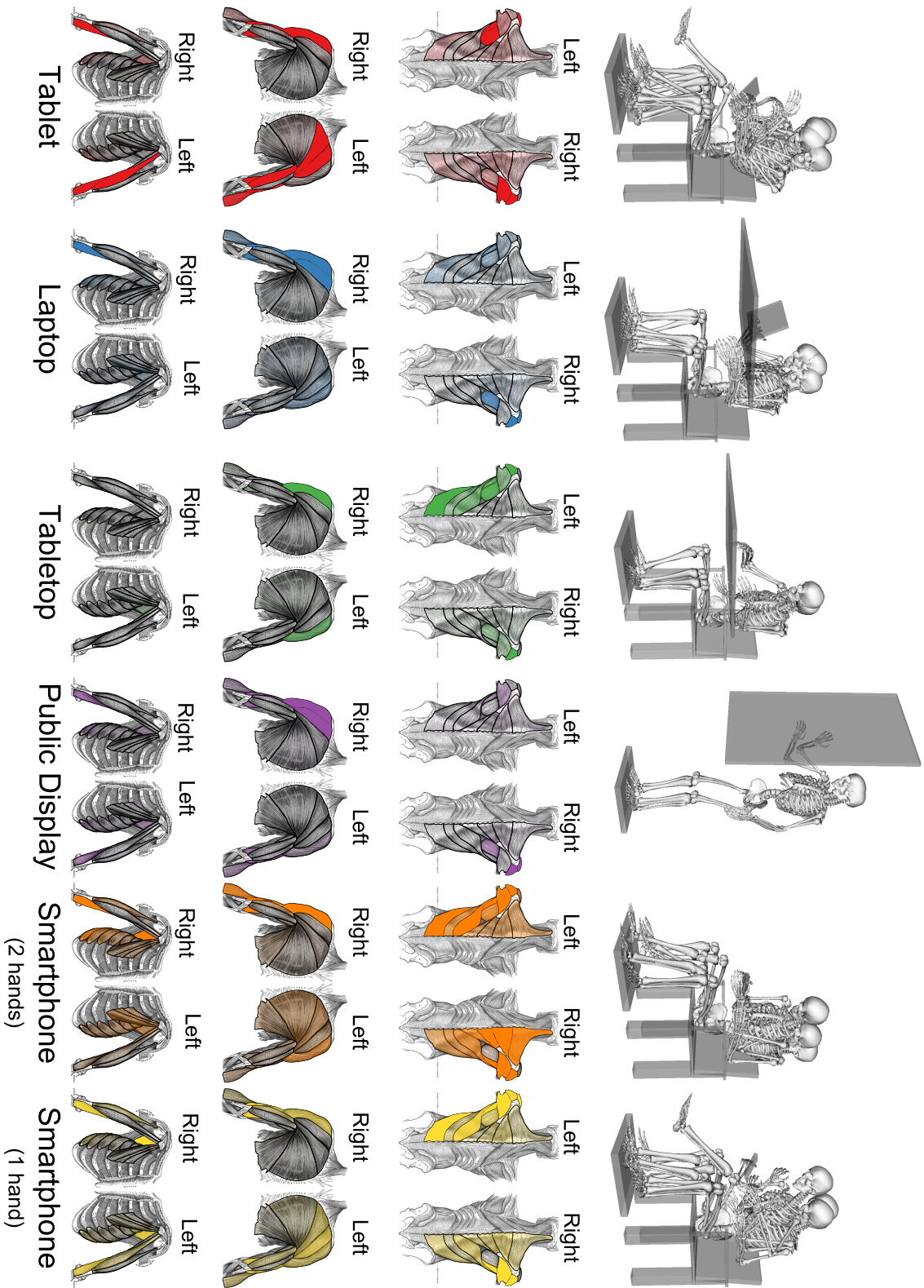


Fig. 6.5: Posture clusters (top) per surface. Total activations of major muscles are shown below per surface type.



deltoids and infraspinatus. The tabletop recruits muscles of the lower back and the medial deltoid of the input arm. The public display, similarly to the laptop, recruits frontal and medial deltoid muscles of the input arm. Additionally, due to the standing posture, it shows higher total activation in all postural muscles. When interacting with the smartphone with two hands, the lower back muscles of the holding arm, as well as the upper back, medial, and back deltoid muscles, are strongly activated. When interacting with one hand, upper back muscles are not that activated, but the medial and back deltoids of the interacting arm are more strongly activated.

### Posture Analysis

Our posture clustering permits insight into differences within surfaces. Recall that users were allowed to take whatever postures they liked. We first report on the postures used by our participants. The clusters are visualized in Figure 6.5.

The following observations can be made.

- **Tablet:** These postures were grouped into six clusters. In the first five, the subjects hold the tablet in their hands in a low position close to their stomach. In the sixth cluster, they hold the surface closer to their face in a higher position. None of the subjects rest their back on the backrest of the chair, while four sit with their legs crossed.
- **Laptop:** These postures were grouped into three clusters. In all three, the subjects keep their left arms under the table and none of them rest their back on the backrest of the chair.
- **Tabletop:** Two clusters were found. In the first, the subjects mainly rest their left arm on the armrest while they perform their task. In the second, they have both arms on the table. Again, none of the subjects rest on the backrest of the chair.
- **Public display:** Two clusters were found. In both, subjects keep their left arm along their body. The main difference is that in the first cluster, the subjects have their trunk closer to the surface.
- **Smartphone, 2-handed:** Three clusters were found. In the first, the subjects rest on the backrest of the chair and place their elbows on

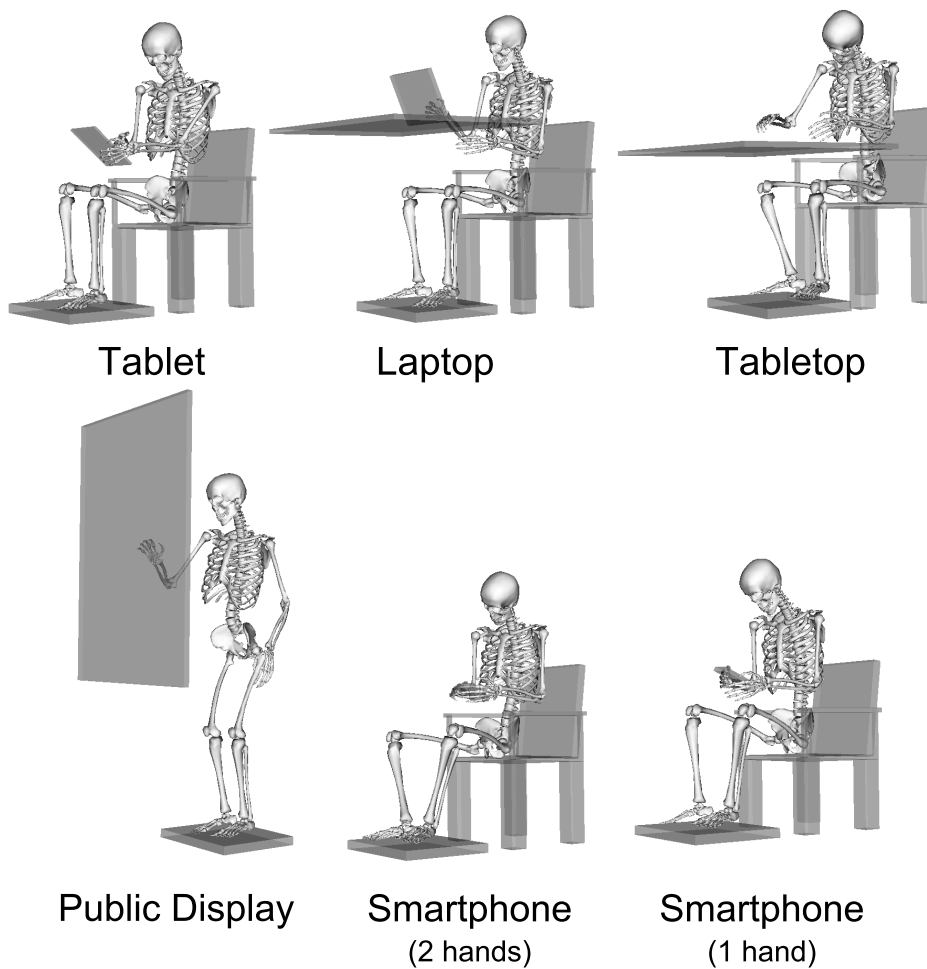


Fig. 6.6: The median postures for each surface type recorded in the study.

the armrests, so that the trunk is oblique with respect to the seat. They keep the phone very close to their face. In the second, they sit instead in a straight position keeping the phone close to their knees. In the third, they sit back on the chair, resting their back. They keep the phone close to their face and their legs are outstretched.

- **Smartphone, 1-handed:** Four clusters were found. In the first, the subjects keep their right elbow on the right armrest and they have their torso bent toward the front. In the other clusters, the subjects sit in an upright position. In the third, the subjects keep their legs crossed, and in the fourth they keep the phone close to their face.

Note that by using the clusters, we can improve the fit of Fitts' law models by 10%. The new goodness scores are shown in Table 6.3. This

## 6.1. Performance and Ergonomics of Touch Surfaces

Cluster \ Variable	Variable	Fitts' $a$ coefficient	Fitts' $b$ coefficient	Fitts' $R^2$	Throughput ( $bits/s$ )	Muscle activation
Tablet	1	-0.34	0.44	0.85	4.39	608
	2	-0.15	0.28	0.97	5.79	569
	3	-0.14	0.30	0.95	5.20	619
	4	-0.15	0.27	0.78	5.40	602
	5	-0.16	0.29	0.84	4.99	627
	6	-0.37	0.46	0.62	4.67	1561
	7	-0.27	0.37	0.54	4.45	522
Laptop	1	-0.15	0.29	0.97	5.08	597
	2	-0.18	0.28	0.97	5.39	549
	3	0.04	0.21	0.82	4.67	600
Tabletop	1	-0.52	0.30	0.97	7.41	710
	2	-0.48	0.30	0.94	6.84	686
Public display	1	-0.47	0.31	0.96	6.24	1025
	2	-0.41	0.29	0.94	6.27	849
Smartphone 2 hands	1	-0.57	0.34	0.96	6.42	672
	2	-0.46	0.29	0.89	7.42	616
	3	-0.42	0.24	0.98	8.54	357
Smartphone 1 hand	1	-1.20	0.56	0.91	5.72	632
	2	-0.58	0.36	0.96	6.09	578
	3	-0.67	0.42	0.93	4.92	755
	4	-0.45	0.29	0.95	6.83	236

**Table 6.3:** Performance and ergonomics indices for posture clusters.

is in line with the idea that muscle groups affect Fitts' law model parameters. By decreasing heterogeneity in postures we can therefore also improve model fit. This effect is not achieved by arbitrary reclusterings, for example per user only.

### 6.1.6 Discussion

The study has demonstrated that although touch interaction on different surfaces is similar, there are in fact large differences, in particular with respect to ergonomics. The differences in performance are also large, but not extreme, so with respect to performance all surfaces can be used for interaction even with high IDs, without degrading throughput too much. In contrast to performance, differences in ergonomics can be as large as

2-fold on an aggregated level over the whole body, for example in the case of the public display and smartphone, and 6-fold on an aggregated level over body regions, for example the neck loads. Thus, our finding with respect to ergonomics has to be considered when designing an application for multiple devices.

We summarize the observations as follows:

- The tablet has poor performance and is suitable for long-term use only after adjustment of the pose to avoid neck problems.
- The laptop has mediocre, almost poor performance, but it is suitable for long-term use.
- The tabletop has high performance, but it is not suitable for long-term use, unless proper posture support is provided.
- The public display has high performance but it is not suitable for long-term use.
- The smartphone used with two hands has high performance but it is unsuitable for long-term use.
- The smartphone used with one hand has medium performance and is also unsuitable for long-term use.

The dataset is available for the research community, and here we provide slightly deeper discussion only for the laptop and public display. The interaction with these surfaces is performed through movements of the arm, but they differ with respect to postures and performance. In interaction with the laptop the posture varies slightly, and most participants tend to minimize muscular load and keep the arm posture as close to the neutral posture as possible. The most used muscles are muscles of the shoulder and arm, and in contrast to expectations, the laptop provides the lowest total muscle activations with acceptable throughput, which means that it can be used for a prolonged period. The interaction with the public display involves postures with much higher muscle activations, involving shoulder, back and arm muscles much more strongly, but providing slightly higher throughput. Additionally, the movements involved with public display interaction are much longer than with the laptop, which leads to even higher total muscle activations, in particular when

reaching targets higher on the screen. Thus, as expected, the public display is not suitable for prolonged interaction, and will lead to “Gorilla arm”.

To contextualize our findings, we qualitatively compared them with previous studies. Similarly to Barbe et al. [123], our results confirmed significant differences among different postures. Although the conditions cannot be directly compared, the laptop in front of the user in our study demonstrated the lowest fatigue index among conditions, agreeing with Barbe et al.’s “tilted display.” The recruitment of shoulder muscles in the tablet condition varied with respect to posture and the presence of support, and the upper trapezius on the dominant side was more activated than on the non-dominant side, as in the study of Young et al. [126]. Similarly to Oehl et al. [142], we observed an effect of display size on throughput for tilted and horizontal displays, but not for handheld and vertical display conditions. As in the study of Wagner et al. [373], we observed different grips during the experiment, including both “novice” and “expert” grips. However, in our case users were seated, and they often adjusted their posture and supported the tablet with their knee or leg.

As we can see, the motion capture-based biomechanical simulation provides new insights concerning interaction. In contrast to traditional methods, the straightforward application of the proposed method makes it possible to conduct broader studies involving more interface alternatives, comparing them or tuning some design parameters. While the gains in insights with respect to performance only are not much larger compared to traditional performance measurement methods, the gains with respect to ergonomics as well as with respect to interactions between performance and ergonomics are much larger.

Theoretically, by using traditional methods it could be possible to get many of the variables generated by our method, possibly even with slightly higher reliability and details of individual variables due to directness of measurements. However, it would necessitate multiple separate experiments and experimental set-ups, which would significantly reduce comparability between the data recorded in separate setups and sessions, as well as overall interpretability of the data. To benefit from direct measures of individual variables, it would be better to perform direct-measure experiments only in a second run—localized on a particular segment of human body and focused on the variables with the most interesting dif-

ferences, while using motion capture-based biomechanical simulation in the first run to identify general patterns and the most interesting variables.

## 6.2 Physical Ergonomics of Tablet Interaction<sup>2</sup>

### 6.2.1 Introduction

In this section we expand our analysis of the ergonomics of tablet interaction. The analyses are performed on the dataset described in the previous section. We present a physical ergonomics assessment of typical tablet device usage. Tablet devices are becoming widespread and often even displace personal computers and laptops. However, while the physical ergonomics of PCs and laptops was extensively studied in the past, there is only a little knowledge of the ergonomics of tablet devices. In particular, the user assessment is complex due to the portability of tablets, which allows a variety of tablet locations, orientations and ways of holding them which can be adopted by users. The purpose of this work was to identify typical postures, the set of recruited muscles and health risks related to the tablet interaction.

A few previous works [126, 375] have measured head and neck posture, or wrist and shoulder posture of tablet usage, but they used a predefined set of tablet hold configurations. They extracted joint angles directly from locations of markers attached to anatomical landmarks, which ignores such sources of error as marker drift during movement, joint displacement, or absence of skeletal anatomy. In contrast to this, we do not assume a particular posture for interaction and ask participants to take a pose and hold the tablet as is comfortable for them. We record motion of the whole human body and analyze biomechanical indices simulated using an anatomically-correct musculoskeletal model.

### 6.2.2 Methods

For the analyses we used the TOUCHCORPUS dataset described in the previous section. We use Matlab and an interactive visualization tool [362] to

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<sup>2</sup>This chapter is based on the paper *Physical ergonomics of tablet interaction while sitting* [374]

## 6.2. Physical Ergonomics of Tablet Interaction

Body part	Biomechanical indices					
	Av. j. angle	Av. j. moment	Peak j. moment	Peak m. force	Av. m. force	Stress level
Neck	-31.5°	2.9N · m	411.9N · m	260.4N	20.2N	High
Supporting shoulder	38°	2.3N · m	184.8N · m	2588.8N	83N	Moderate
Supporting arm	59.8°	1.2N · m	46.1N · m	2006.9N	73.8N	Low
Interacting shoulder	19.2°	1.5N · m	208.8N · m	2351.7N	77.5N	Low
Interacting arm	110.4°	1.8N · m	137N · m	2010.2N	53.2N	Low

**Table 6.4:** Biomechanical indices for tablet interaction.

perform deeper and more specific analyses on the data. We compute average postures of each joint and compare them to movement ranges and neutral postures. Postures close to extreme are considered as a health risk after prolonged use. Further, we consider average and peak joint moments. High values of average joint moments pose health risk after prolonged use; high peak moments can lead to an injury even in brief interaction. We consider peak muscle forces as a factor that can lead to a muscle or tendon injury. High average muscle forces lead to muscle stress and fatigue. In our analyses we focus on the body segments most affected by the tablet usage: upper back and neck, shoulder and arm supporting the tablet, and shoulder and arm interacting on the device. The most extreme value at each segment defines the health risk for the whole segment.

### 6.2.3 Results & Discussion

The overview of aggregated results is shown in Table 6.4. The results show that the typical posture selected for interaction with a tablet is incorrect and has a high risk for users' health. In particular, the posture of upper back and neck is stressful and imposes serious risk: the average neck flexion differs by 42.6° from the neutral pose. Average and peak joint moments are also high for the neck, which can lead to RSI after prolonged use, or to an acute injury in the neck joint. Average muscle forces are moderate, which means that muscles are not actively recruited to support the head and will not suffer from fatigue, but the peak muscle force is high, and can lead to injuries in the neck extensor muscles.

The average elevation angle of the supporting shoulder is slightly larger than neutral zone, so the joint angle is not extreme, but muscles can fatigue after a relatively short period. The average joint moment at

the shoulder is high, which can lead to RSI after prolonged use, but the peak joint moment is moderate; as a result, an acute injury is less probable. Average muscle force is high, and as a result muscles will fatigue relatively fast. Peak muscle force is also high, which can lead to a muscle strain. The elbow joint is in the neutral zone. The average joint moment is low and the peak moment is also low. Average muscle force and peak muscle force are high for some muscles; however, there are redundant muscles with similar action which can be recruited if necessary; for example the biceps can generate force if the brachialis is fatigued. There is no such reserve for the shoulder muscles to recruit in the case of fatigue.

Average shoulder elevation of the interacting arm is in the neutral zone. Average and peak joint moments are moderate; the average moment is 35% lower than the moment of the supporting shoulder. Average muscle forces and peak muscle forces are only slightly lower than in the supporting shoulder, but the set of recruited muscles is different and there is more variability in recruitment. As a result, the muscles of the interacting shoulder can be fatigued, but much more slowly than in the supporting shoulder. Average elbow flexion is  $110.4^\circ$ , which is at the edge of the neutral zone. Average and peak joint moments are moderate. Average muscle forces are low, but peak muscle forces are still high for some muscles. There is more variability in muscle groups of the interacting arm. This adds to more balanced usage of the musculature without exhaustion of a particular muscle.

To sum up, the largest risks of tablet interaction in the typical postures are related with bad neck posture and fatigue of the supporting shoulder muscles. Both device manufacturers and users need to be aware of the risk and should minimize it using the following recommendations.

For device manufacturers:

- Limit the weight of the device, as a lower weight would allow users to hold the device in a correct posture for a longer period.
- Support better grip over the device: in addition to the bezel, also over the touchscreen area.
- Provide options for different external supports for the device, which would allow fixing it in the environment instead of holding it in the hand.

For the users:

- Increase awareness of your posture used during the interaction, and the corresponding health risks.



- Try to use correct posture during prolonged interactions.
- Use external supports to fix the device in the environment, or to support your arm.
- Vary the posture of the holding arm, and shift the device towards the right or left over time; this would allow slightly more rest for the muscle groups supporting the device in each posture.

## 6.3 Summary

In this chapter the motion capture-based biomechanical simulation was used for analyses of real HCI problems. The described examples demonstrate the richness of the produced biomechanical data and its value for the HCI field. The insights derived from the data provide new, often counterintuitive information concerning the effects of interest.

The first part demonstrated the relationship between performance, ergonomics and touch surface type. The interesting finding is that the interaction with the laptop with a touchscreen provided the best total energy expenditure, even better than the tablet. With respect to performance the 2-handed smartphone and tabletop were in the lead, though with a relatively small advantage. Another counterintuitive result showed the absence of a trade-off between total energy expenditure and input performance, which means that by optimizing for high performance we simultaneously minimize ergonomics cost.

The second part demonstrated the size of the problem related to excessive neck flexion while interacting with a tablet. While it was known before that excessive flexion poses a risk to human health, only the simulation allowed us to compute that on average 95% of users interacting in a bad posture impose 5 times larger neck loads than those interacting in an optimal posture.

To conclude, this chapter has responded to **Research Questions 2.1, 2.2 and 2.3** by:

- providing new insights with respect to performance through comparison of touch surfaces, and showing up to 30% differences between the conditions.
- providing new insights with respect to ergonomics through comparison of touch surfaces as well as deeper analysis of tablet ergonomics, and showing 2-fold differences in total muscle activation

(index of energy expenditure), as well as 5-fold differences in joint moments (mechanical loads) at the neck.

- providing new insights on interaction between performance and ergonomics, namely demonstrating that instead of a trade-off between these factors, there is a synergy—by maximizing performance we simultaneously minimize total muscle activation.

# Chapter 7

## Lowering Barriers for Non-Experts: Overview of the Full-Arm Movement Space through Muscle Co-Activation Clustering<sup>1</sup>

### 7.1 Introduction

This chapter considers **Research Questions 3.1 and 3.2**. We have already demonstrated that motion capture-based biomechanical simulation is a technically applicable and valid method which can provide HCI researchers and practitioners with new insights with respect to performance and ergonomics of post-desktop input methods. However, while being more feasible and informative than other HCI methods, the proposed method is still complex to apply. Additionally, while it can be directly applied for summative studies (interface prototype evaluations and comparison of alternative designs), there is a lack of support for formative studies (research on the design space and informed generation of design alternatives).

In this chapter we approach the above-mentioned problems through development of a summarization of performance and ergonomics of move-

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<sup>1</sup>This chapter is based on the paper *Informing the Design of Novel Input Methods with Muscle Coactivation Clustering* [332]

ment space in a set of equivalence classes. Considering the recommendations for motion capture-based biomechanical simulation, we have chosen to investigate whole-arm aimed movements in mid-air. Mid-air interaction has recently become attention in HCI due to development of computer vision and tracking technology. A few examples of recent works in this research direction are medical image exploration [376], tabletops [365], hand articulation interactions [377], large interactive displays [378,379], projector phones [155], video gaming, exergames [380], and rehabilitation [381].

Our equivalence classes summarize performance and ergonomics of whole-arm aimed movements by associating these aspects with the physiological bases of these movements, namely muscle groups activated to execute a movement and corresponding muscle activation patterns. Such summarization is useful for HCI, as it directly includes various measures of the two most important factors—performance and ergonomics.

Formally, equivalence classes (or clusters) refer to “patterns whose distribution in feature space is governed by a probability density specific to each cluster” [382] (page 7). In our particular case, the clusters are understood as *muscular equivalence sets* of aimed movements that are similar in the time-dependent muscle coactivation patterns in an upper extremity of the human body. The clustering concerns the time-dependent activation signal of 41 muscles of the upper extremities in pointing movements. Every movement in this dataset is mapped to one cluster, for which we also compute standard indices of performance (speed, accuracy, throughput) from the optical tracking data. The clustering is based on a novel dataset where muscle coactivations are estimated for real 3D pointing performance of an athlete uniformly covering *the whole reachable space* of the arm: 72,000 movements altogether. To our knowledge, this is the most comprehensive dataset of this kind; as we explain later, it covers many scenarios of novel user interfaces.

The clusters capture the largest trends in the highly *non-uniform* motion space of the human arm. Previous work has demonstrated that the space of pointing movements in general is *non-uniform* with respect to location [338], direction [339], performance [261,266,343–345,383] and involved muscles [340]. Because muscles differ in size, fiber distribution, and force-length-velocity properties, they are differentially recruited in movements in terms of force, timing, moment and acceleration. A movement of the arm on the left-hand side of the torso will recruit a different subset of the muscles than a movement on the right-hand side. Our goal

is to find a minimum number of interpretable clusters that capture such variability in the whole reachable space of the arm.

We assume in our clustering that the main body part responsible for movement is muscle. Human movements are produced by neural impulses (action potential) transferred by the neural system to muscles, similarly to electric current. Muscles react to action potential by contraction to produce an active force. Forces produced by groups of muscles working at a particular joint sum up to produce total moment at the joint. Finally, under the action of moment the joint rotates, producing visible movement. Thus we can see that muscle activations contain all necessary information describing a movement. Thus we do not predefine classes in any way, but compute them in a pure data-driven approach based on muscle activation patterns. Additionally, the approach to build classes based on muscle co-activations is physiologically plausible according to the synergy hypothesis of motor control [384]. However, we do not claim the clustering as a motor control hypothesis, to keep it simpler and practical for HCI. We demonstrate that the clustering not only summarizes complex movement space with respect to physiological and biomechanical factors, it also improves fit of Fitts' performance models within each cluster, meaning that the data inside a cluster is more homogeneous than in the general dataset.

This chapter builds on previous work from HCI and motor control, and broadens it by:

- collecting an extensive dataset of aimed movements uniformly covering the whole space reachable by the arm;
- augmenting the dataset with activation data of all the main muscles of the upper extremity, including the ones not accessible by previous analysis methods;
- associating pointing performance, location in 3D space and ergonomics properties of movements with muscle activation patterns; and
- summarizing a complex dataset with multi-source data in a single simple-to-understand clustering.

The clustering can be used in interface design and research as a heuristic, which provides rough ergonomic and performance characteristics for a movement type of interest. Conversely, it can be used as a summary of the arm movement space, and necessary movements or movement areas

can be chosen based on required performance or ergonomic properties. We demonstrate the effectiveness of clustering on a few examples of real HCI design tasks.

In this chapter we focus on whole-arm aimed movements, but the approach to clustering is general enough to be used for other types of movement spaces, for example for fine-grained finger movements or leg movements, and more complex movement types, for example trajectory-based tasks.

## 7.2 Data Collection

To cover all aimed movements within the reachable space of the arm, we collected optical motion tracking data of the 3D pointing performance of an athlete. The dataset contains 72,000 movements between 25 targets uniformly covering the whole reachable space of the dominant arm.

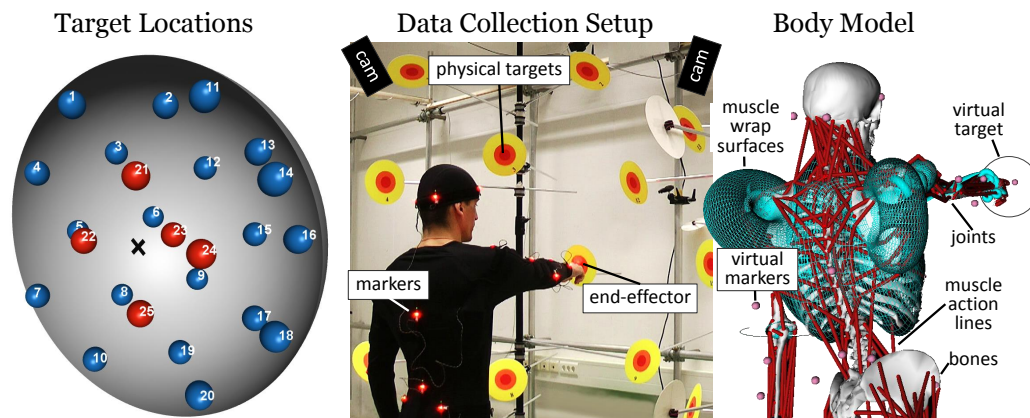
We tracked the full-body motion of the subject during the movements. Motion capture data of the full body allows us to perform biomechanical simulation of recorded movements to look at the indices inside our body: joint angles, moments and forces at joints, forces exerted by muscles and muscle activations [17]. This data can be also used as an estimation of energy expenditure and fatigue indices for each movement.

The data collection setup with the 25 targets is shown at the left in Figure 7.1. Since we use targets with three different sizes (yellow, orange, and red in the figure), and include varying target-to-target distances, the data allows for the computation of performance models.

The athlete is an amateur kickboxer: this sport emphasizes stamina and hand-eye coordination. Hence, the dataset estimates the upper bound of performance reachable by regular users. By studying aimed movements to *physical targets* with no intermediary input device, we can study the performance directly, without the typical limitations of devices such as dwell-time, visibility of the user interface, or latency of cursor updates.

### 7.2.1 User Study

**Participant:** The subject is a 27-year-old male (right-handed, 180 cm, 72.5 kg) with no known health problems. During the last five years, he placed first in the French and German amateur kickboxing competitions. However, he is a well-balanced athlete and regularly does different types of



**Fig. 7.1:** Performance was recorded for all reciprocal pointings between 25 targets (left) covering the reachable space of the arm. To allow biomechanical simulation, optical markers on the subject's body (center) are mapped via anatomical landmarks to a generalized model of the human (right). Physical targets are registered in the virtual 3D space to allow the computation of performance metrics (speed, accuracy, and throughput).

training besides kickboxing: athletics and running, push-ups and pull-ups, cycling, swimming, hiking and dancing. The fact of balanced training implies that recruitment of his muscles is similarly distributed as that of average people, which is confirmed against 16 other subjects (Section 7.2.2). However, regular training implies that all muscles are stronger, so his data would correspond to skilled user performance.

**Movement targets:** Figure 7.1 (left) shows the reachable space studied: a half-sphere with radius equal to the subject's arm length and centered at the right shoulder's pivot point. The targets were distributed over the 3D space by means of a densest sphere-packing algorithm. They were created from cardboard disks of three colors (yellow, orange, and red) that correspond to three target-width conditions, with radii of 8 cm, 4 cm, and 2 cm, respectively. These were attached to the ends of aluminum pipes. To ensure that the shoulder stays at the center of the sphere, we prevented leaning with a horizontal obstacle placed about 2 cm in front of the chest.

**Experimental design:** We have selected aimed movements as a basic movement type ubiquitous in HCI, which can additionally serve as a base for trajectory-based gestures. The experiment consists of 80–85 aiming movements carried out for all pairs of the 25 targets, each with three target-width conditions (2, 4, and 8 cm). This yields a total of 72,000

pointing acts. The order of trials was randomized in the experiment.

**Procedure:** Thirty sessions of 90–120 minutes each were carried out over three weeks. The subject stands in a position marked on the floor and repeatedly moves between two given targets as accurately and quickly as possible. Before each target pair, the subject can find the best manner of aiming at the targets. Timing starts with the index finger on a target. After a trial, if the self-reported fatigue level is high, five minutes of rest is required. All movements were made with the subject’s dominant hand. We imposed a minimum recovery interval of six hours between sessions to allow fast twitch muscle fibers to restore their potential energy.

**Apparatus:** The *PhaseSpace* system with 12 Impulse cameras at 480 fps was used to record the movement of 38 active markers (Figure 7.1, center). Marker placement was done with care to minimize drift during a session. The tracking accuracy is approx.  $1/5$  mm.

**Data processing:** The data processing was performed according to the pipeline described in Chapter 3.

### 7.2.2 Validation

Because our analysis is based on a single participant, a trained athlete, we wanted to confirm that his movements do not differ significantly from those of “regular users”. The fact that the participant performs balanced training in different sports is very important here, since this way he trains not only some particular muscle, but all muscles of his body uniformly. Hence, his muscles are proportionally more powerful than the muscles of an average person, but he recruits them in a very similar way. To this end, we acquired a recently published dataset that used exactly the same experimental setup and task with 16 participants (9 m, 7 f, mean age 26, mean height 170 cm, mean weight 70 kg) [313]. The task is otherwise the same, but a stratified sample of five targets was used per subject (the athlete dataset has 25 targets).

To compare movement style between the athlete and the sixteen participants, we computed correlations for marker positions, movement velocity, joint angles and moments. The obtained correlations show that although the athlete was much faster at the task, the movement style was very similar: absolute position ( $r = 0.98$ ), absolute velocity ( $r = 0.97$ ), joint angles ( $r = 0.87$ ) and joint moments ( $r = 0.75$ ).



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## 7.3 Overview of the Dataset

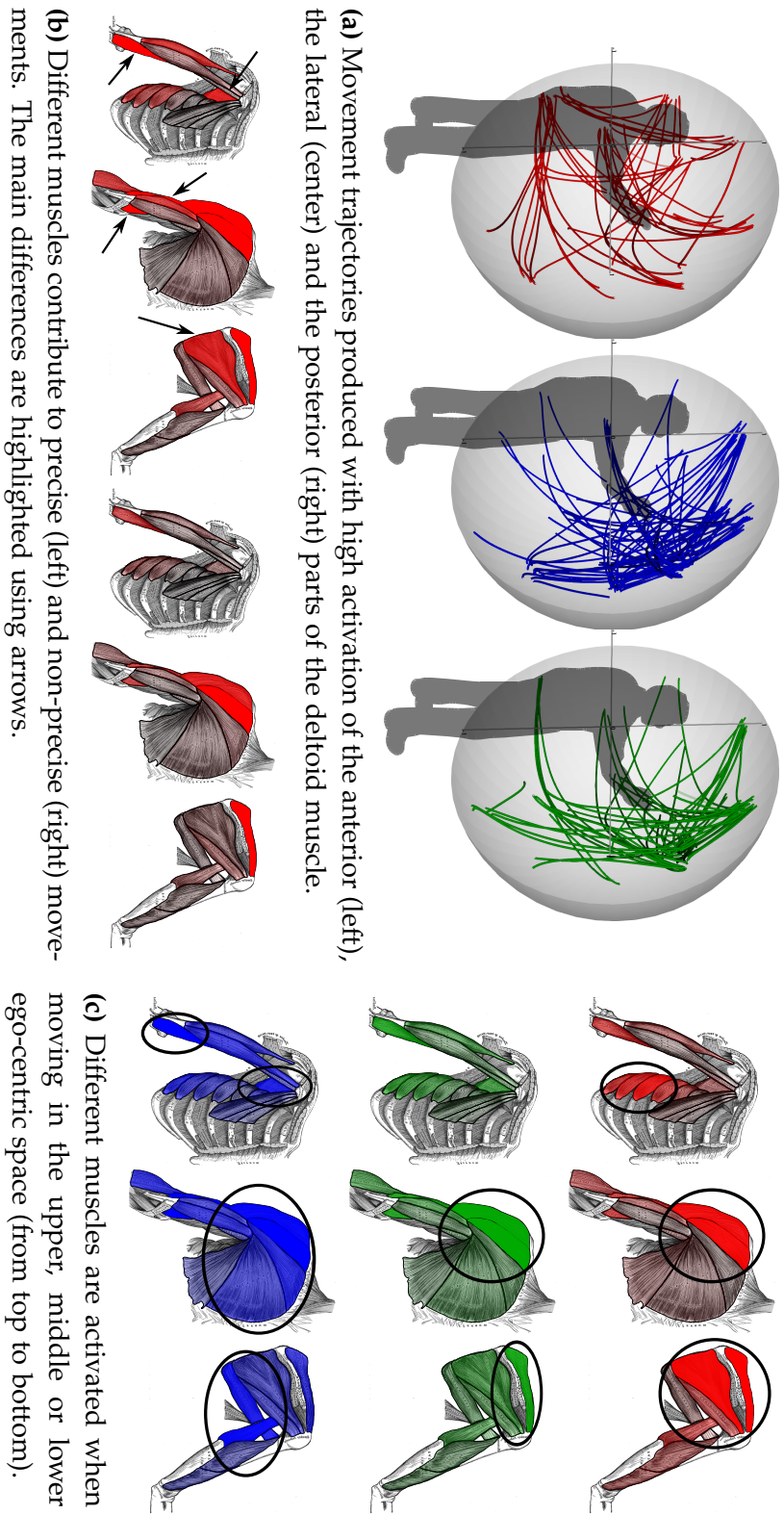
The obtained dataset provides a rich description of human movement when pointing in 3D. It contains over 400 variables describing complex interrelations between spatial locations, performance, and ergonomics:

- **spatial information:** 28 variables including target positions and sizes, trajectories of the end-effector, velocity, acceleration, directionality in polar coordinates and angles of projections on two vertical planes and with origin at the shoulder center;
- **performance:** 17 variables including accuracy, movement time, effective target width, index of difficulty, Fitts' law model parameters and coefficient of determination, throughput;
- **ergonomics:** 361 variables including moments and forces for 21 joints, forces and activations for 41 muscles per frame, as well as corresponding aggregated values for complete movements.

We briefly present an overview of the dataset here, before proceeding to the clustering method in the next section. Table 7.1 provides a full dataset description.

Figure 7.2 shows the non-uniformity of aimed movements in 3D, particularly with respect to ergonomics. For example, the three parts of the deltoid muscle of the human shoulder are extensively used when pointing in 3D, but each of them has a distinct spatial activation pattern. Figure 7.2(a) shows that the movements with the highest activation of the anterior deltoid are found in the left half of the movement space, while the lateral and posterior deltoids have different patterns in the right and top-right corner.

Figure 7.2(c) shows how different muscle groups are activated when performing in the upper, middle, and lower parts of the ego-centric space. Both examples show that there is a strong connection between the activation of muscles and the spatial location of the performance. Figure 7.2(b) shows that there is also a strong relation between performance and ergonomics. We bisected the dataset into movements with high and low precision by splitting it on mean accuracy, and visualize the muscle activations for these two sets. It can clearly be seen that specific muscles are more activated in order to produce precise aimed movements. Again, this confirms the non-uniformity of aimed movements in 3D.



**Fig. 7.2:** Overview of the non-uniformity in the dataset. The three plots show how aimed movements with different properties. Color saturation in (b) and (c) indicates the strength of the muscle activation.

Variable	Count	Aspect
Subject's age	1	Case
Subject's height/weight	2	Case
Other case studies' dependent variables	N.A.	Case
Size of targets	1	Case/Physical Space
UI setup	7	Case/Physical Space
End-effector 3D coordinates	3	Physical Space
End-effector velocity	3	Performance
Velocity angles	2	Performance
End-effector absolute velocity	1	Performance
Mean movement velocity	1	Performance
Movement offset	1	Performance
Index of difficulty	1	Performance
Effective index of difficulty	1	Performance
Movement time	1	Performance
Mean movement time	1	Performance
Throughput (4 types)	4	Performance
Generalized coordinates	21	Ergonomics
Moments at joints	21	Ergonomics
Integrated moments at joints	21	Ergonomics
-// - normalized over movement length	21	Ergonomics
Forces inside joints	90	Ergonomics
Forces exerted by muscles	41	Ergonomics
Force integrated over movement	41	Ergonomics
-// - normalized over movement length	41	Ergonomics
Muscle activations	41	Ergonomics
Activation summed over movement	41	Ergonomics
-// - normalized over movement length	41	Ergonomics
Total muscle activations	1	Ergonomics
-// - summed over movement	1	Ergonomics

Table 7.1: Description of all dataset variables

## 7.4 Clustering

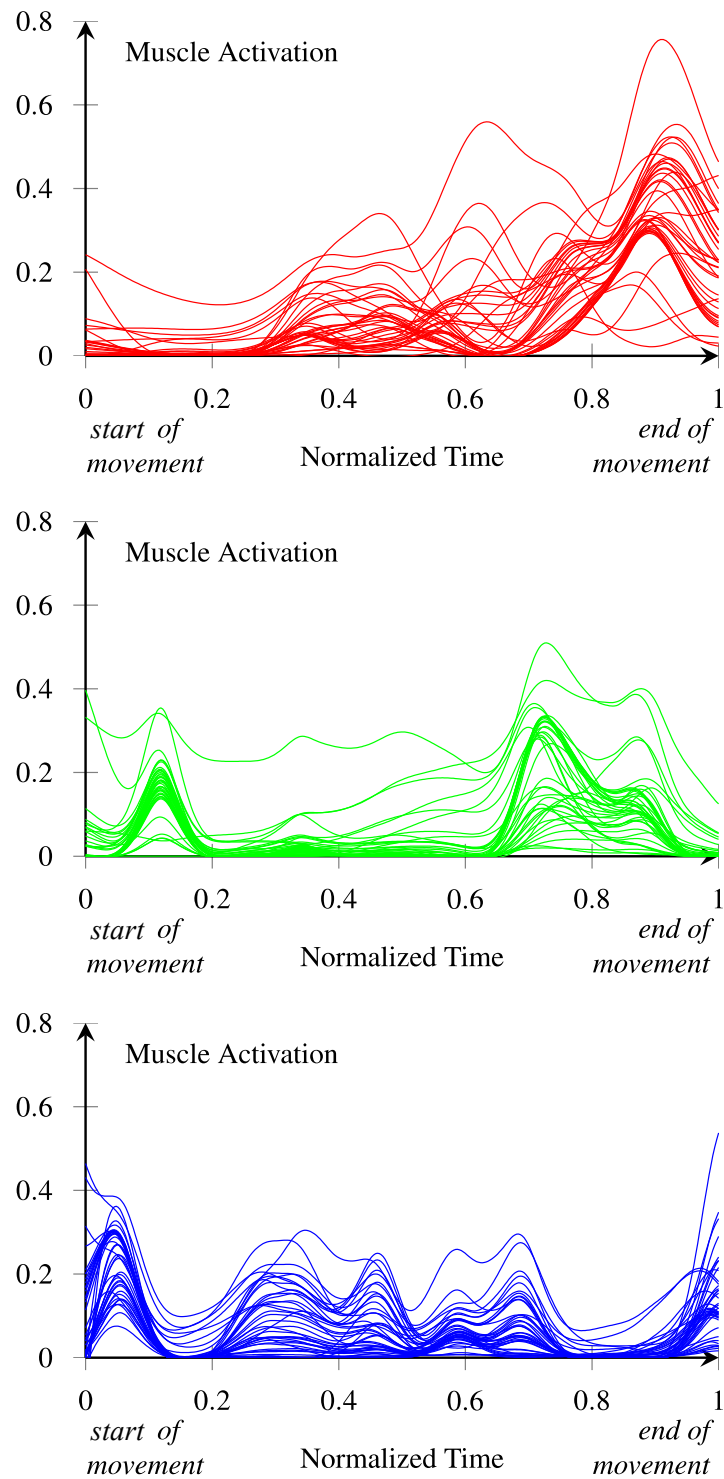
The collected dataset represents aimed movements of all lengths, in all directions and in all locations of the reachable space. In this section, we develop a comprehensive clustering that helps in understanding the ergonomic and performance impacts of design choices. We capture the differences and similarities of muscle activations using the following approach: we cluster all movements based on the temporal muscle activation patterns. Section 7.4.1 explains this in detail. The result is a comprehensive set of 11 clusters—each with distinctive ergonomic and performance costs of aimed movements in specific regions of the ego-centric space (Section 7.4.2). As we will show later in our applications, these clusters are a great resource to include biomechanical information into the design process without running a full-blown study with biomechanical simulation.

### 7.4.1 Method

Muscle activations are time-dependent functions. Our dataset describes each movement with a family of 41 time-dependent muscle activations, one for each muscle. We call this the *muscle activation pattern* of a movement. Figure 7.3 shows these patterns for three movements in our dataset. Note how these muscle activations are changing over time: for example, accelerating the arm recruits different muscles than decelerating.

The goal of clustering is to identify movements which are similar to each other with respect to their muscle activation patterns. In the dataset, muscle activations are represented by vectors of varying length, as initially movements have different time lengths and are sampled uniformly at constant intervals. To allow clustering of activations, we normalize them by time and represent each movement with the same number of samples, namely 40. The samples are computed as mean activations of all muscles within equal length segments and are concatenated into a single vector—this is a compact representation of the muscular activity for each movement, which is later used for clustering. All other analysis steps are performed on the original muscle activations.

We use an agglomerative hierarchical clustering [372], which provides different levels of abstraction and does not impose assumptions about the distributions. We use Euclidean distance for the clustering, because activations at any time or in any muscle have the same effect on the mea-

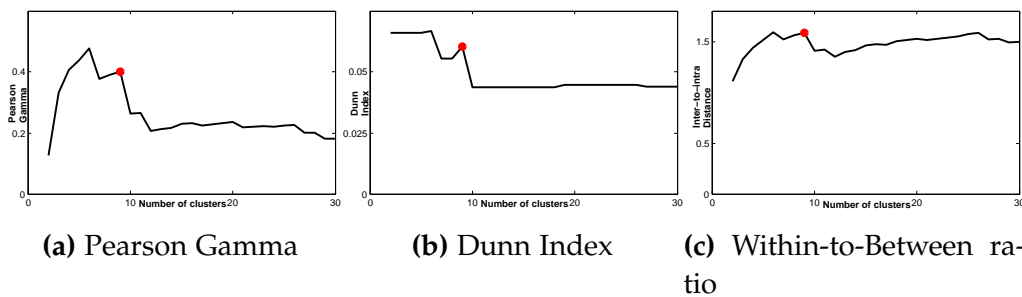


**Fig. 7.3:** Muscle activations of three different movements. A movement is characterized by the time-dependent activation of muscles (here: 41). The clustering is based on these muscle activations and assigns similar ones into the same cluster.

sure. Moreover, absolute values are appreciated, which is important in our setting. In contrast, the Pearson correlation would ignore absolute values. We use Ward's minimum variance linkage method [385], because it creates compact spherical clusters.

In addition, we have tried different clustering methods and distance measures (*k-means*, *hierarchical clustering* with *Ward*, *single*, *complete*, *average* and *centroid* linkage methods, and *Euclidean*, *maximum* and *Manhattan* distances) and compared their results. The clusters created across all distance measures contain much overlap, but the *Manhattan* distance preferred more directionality over co-location in the space, and clusters created with *maximum* distance were less prominent in 3D space than with other distances. We conclude that *Euclidean* distance not only matched our assumptions best, but also performed better than others in production of interpretable clusters. Among linkage methods, differences were more radical. *Single* and *centroid* linkage methods performed the worst: at each level of hierarchy, they add a single movement to one already existing cluster and all non-added movements are considered as separate clusters. *Complete* and *average* linkage methods performed slightly better than *single* linkage, but still they kept most movements in the single cluster and all other clusters contained less than 10 movements each. *K-means* for numbers of clusters near 20 produced clusters which strongly overlap with the clusters identified by the hierarchical *Ward* method, but some of them simultaneously span similar locations in 3D space. For smaller numbers of clusters, *k-means* produced clusters which are hard to interpret. Among methods we tried, hierarchical clustering with the *Ward* linkage method and *Euclidean* distance produced the clusters that were most interpretable with respect to 3D location and direction, and of acceptable size.

For the clustering method we have chosen, Figure 7.5 shows the hierarchy of the resulting clusters in the form of a dendrogram. As can be seen, we selected different levels in the hierarchy for different clusters. This was done in a semi-automatic fashion informed by three quality measures for hierarchical clustering: Figure 7.4 shows the *Pearson gamma*, the *Dunn index*, and the *inter-to-intra* cluster ratio. We have also checked other cluster quality indices such as *average silhouette width*, *Calinski and Harabasz index*, *Goodman and Kruskal's Gamma coefficient*, and *G3 coefficient*, and they show similar patterns by *bumps* or *elbows* on the plot for the particular cluster number. These quality measures show that 6 and 9 clusters are good choices. When choosing 6 clusters, distinctions between



**Fig. 7.4:** Quality measures for the clustering aid in selecting an appropriate number of clusters.

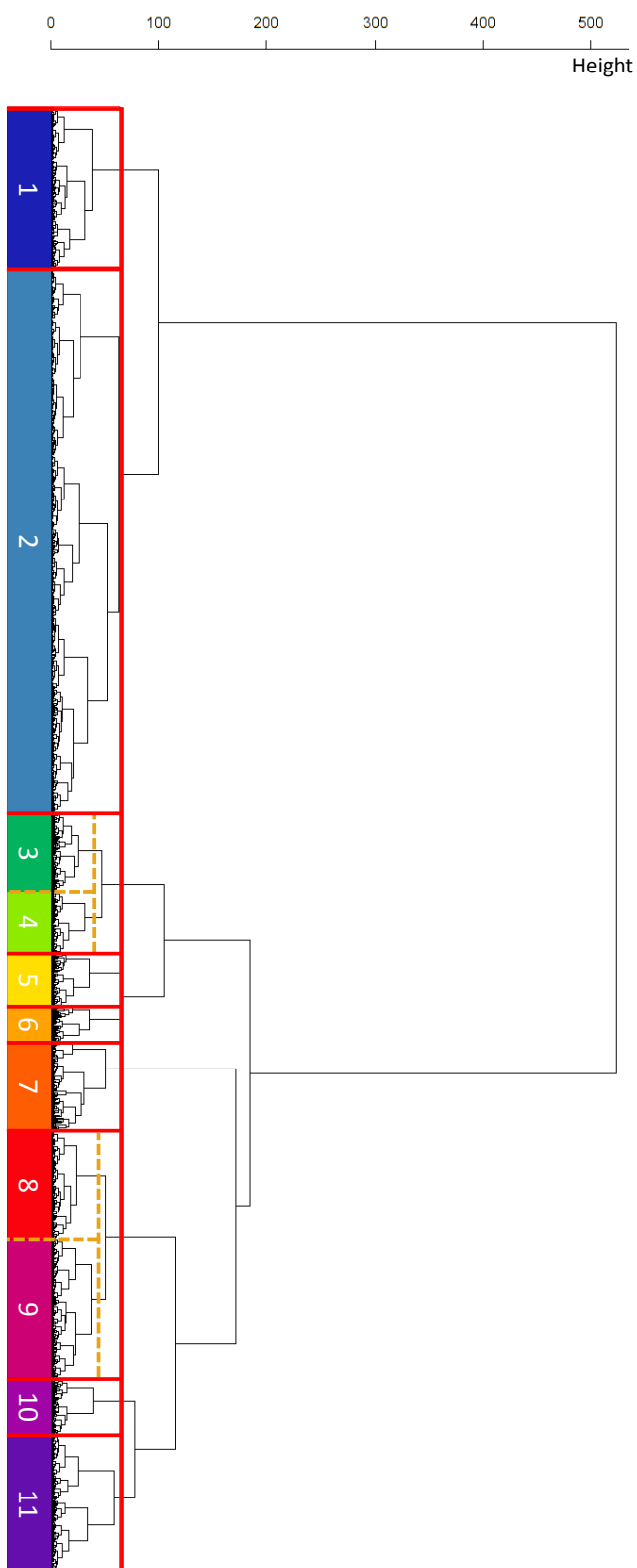
clusters in 3D location and movement directionality are weaker or even degraded; for example, Cluster 5 and Cluster 6 are combined into a single one, although they correspond to movements on opposite parts of space. When choosing more clusters, they become more compact in 3D space and exhibit even more similarity in movement direction, but as a downside multiple clusters start to span the same space, which also affects interpretability. We decided in favor of 9 clusters, since they were more interpretable for humans—this is important, since this clustering is supposed to be read and understood by humans when designing interfaces, rather than by a machine. Finally, we inspected these clusters and split two clusters one more time (by choosing the next level in the hierarchy for them) in order to obtain an even more human-interpretable result, as can be observed in Figure 7.7. The final number of clusters is 11. We have also analyzed the dendrogram at each split to extract any semantic interpretation of why the split occurred. We considered the most prominent differences between mean values of two clusters under the split as a semantic description of the split (Figure 7.6), although small differences were present in patterns of most muscles.

## 7.4.2 Overview of Clustering

Figure 7.8 shows details about the movements in each cluster: their performance, their ergonomics, and their location in 3D, as well as the main directions of the movements. In particular, we show:

- **performance:** two groups of bar plots representing the average movement time and offset. We used black for the overall value and colors for the values of the respective clusters;





**Fig. 7.5:** Dendrogram showing the hierarchical structure of the whole dataset. Red lines cut the dataset into clusters at the height selected by the goodness-of-clustering criteria; orange dashed lines correspond to the cuts performed manually.



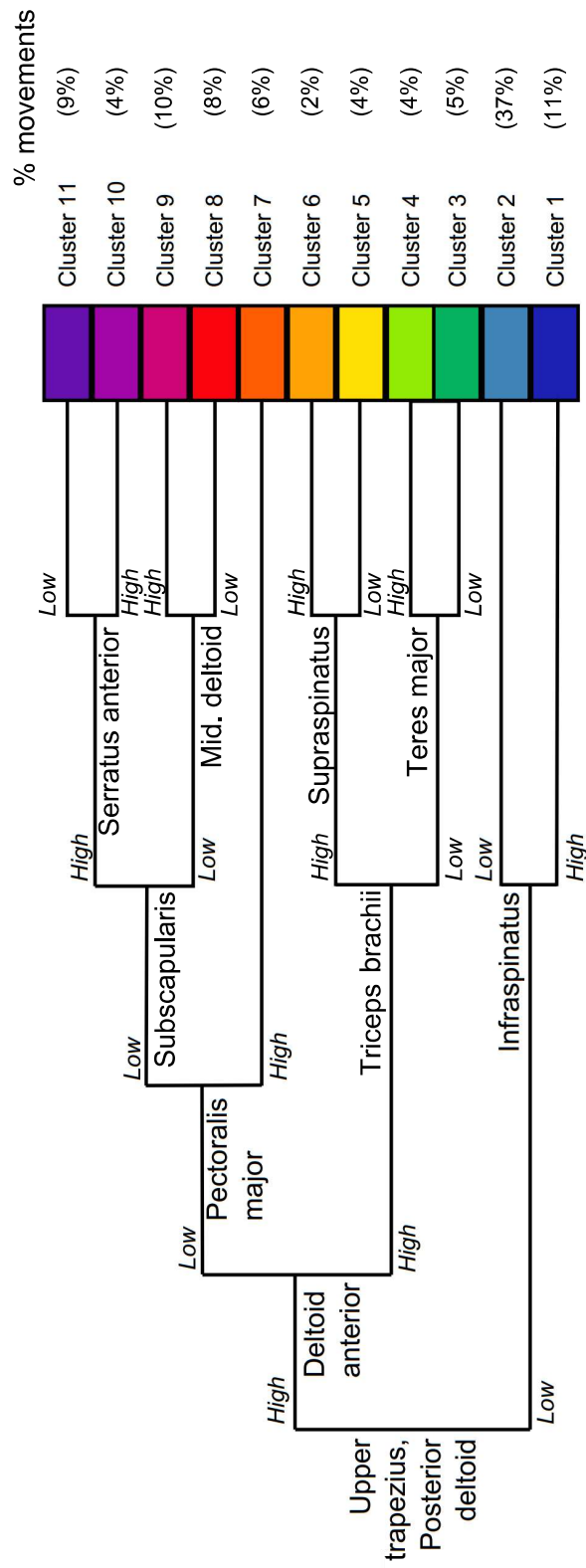
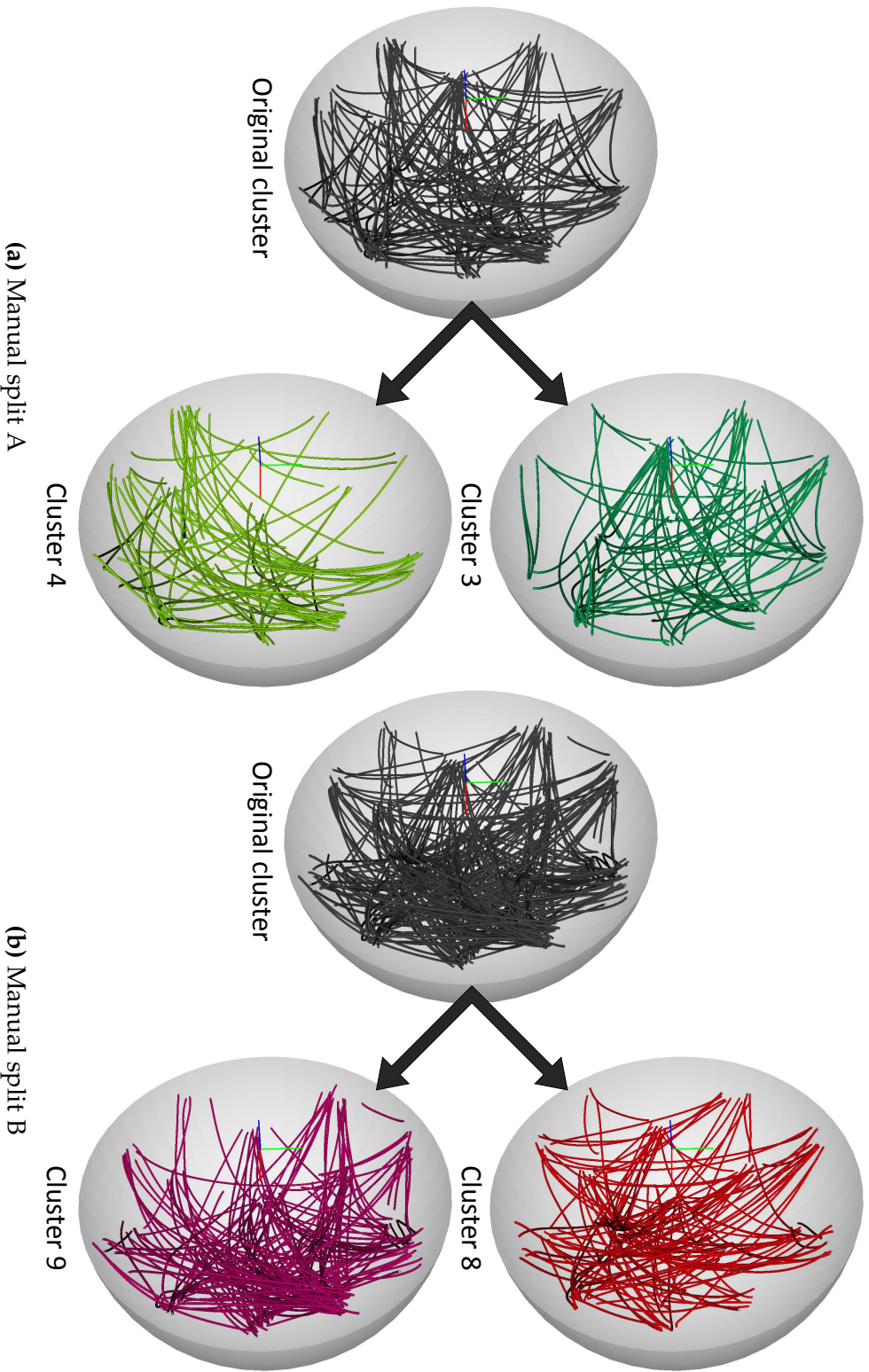
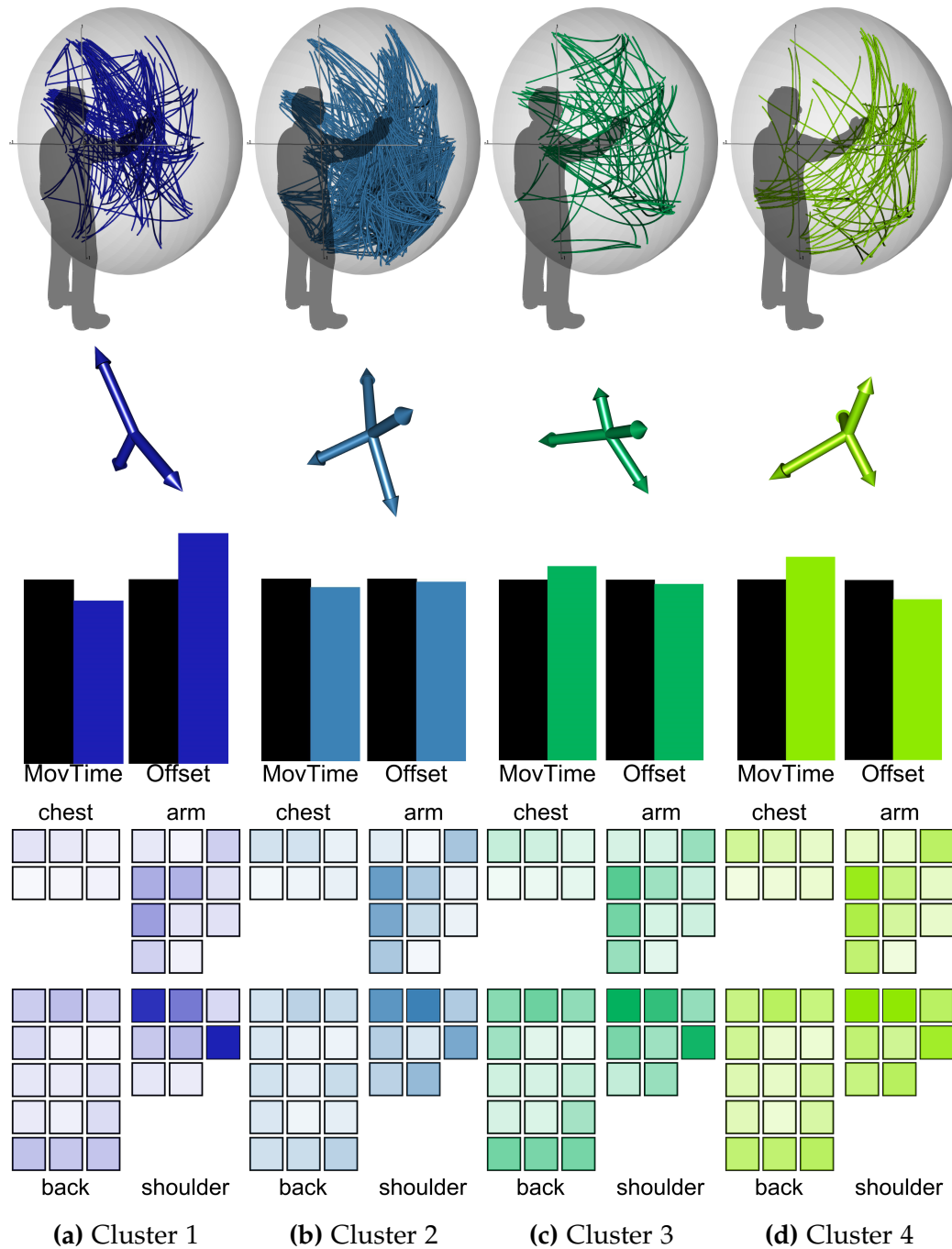


Fig. 7.6: Semantic representation of the dendrogram. The splits in this hierarchy are named after the muscle with the highest activation difference between the split sets. See the text for details about choosing the levels.



**Fig. 7.7:** The clusters are manually split on the next level of the dendrogram to become more interpretable in 3D space and movement directionality. As can be observed in the figure, it is hard to identify any pattern in the original clusters, but after the splits it becomes visible that cluster 3 contains long and middle-length movements in the central and upper part of the space, directed diagonally closer to horizontal; cluster 4 contains long close-to-vertical movements in the right upper part of the space, smoothly transitioning through close-to-diagonal movements in the lower right part of the space, to close-to-horizontal movements in the lower left part of the space; cluster 8 contains long movements between opposite parts of the space; and cluster 9 contains medium and long slightly diagonal and close-to-horizontal movements mostly in the right and central parts of the space.



**Fig. 7.8:** Each subfigure shows performance (barplots), ergonomics (LED visualization) and spatial information (3D trajectories and oriented arrows) for the final 11 clusters. The opacity of each LED is defined according to the average activation of the corresponding muscle in the current cluster. See the last part of this figure for the legend. (continued)

Overview of the Movement Space through Muscle Co-Activation Clustering

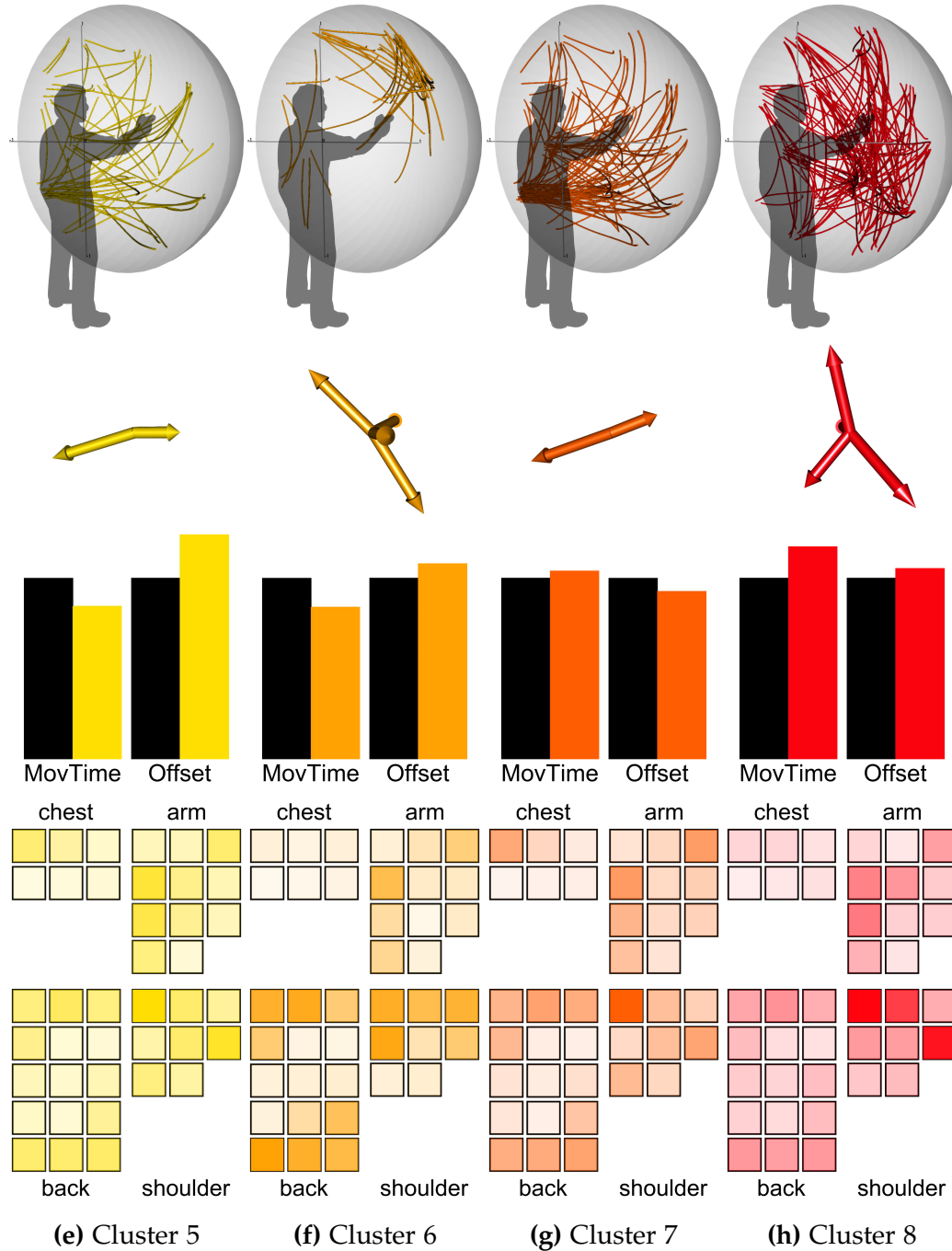
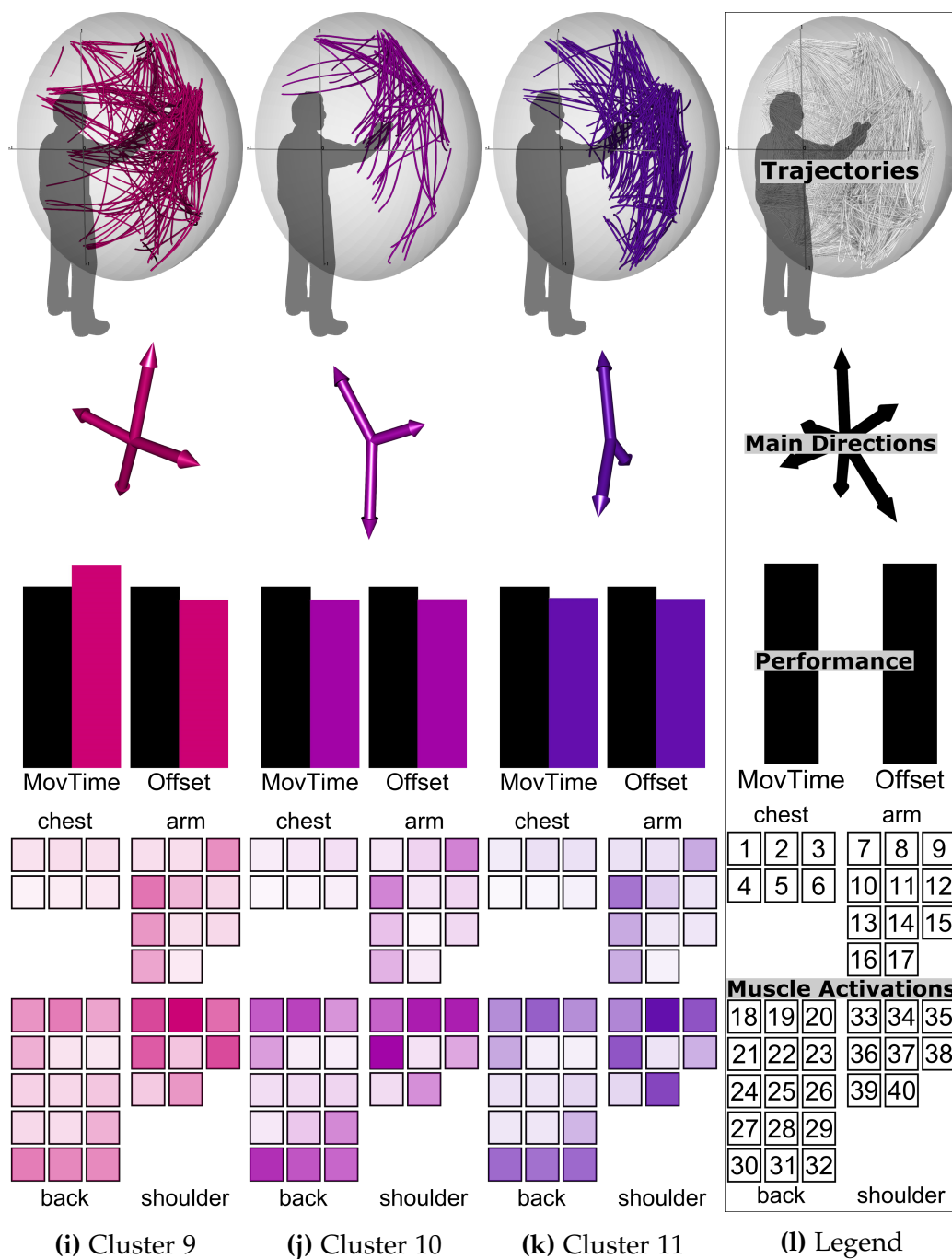


Fig. 7.8: (continued)



**Fig. 7.8:** (continued) The muscles represented in the LED visualization are: 1–3 Pectoralis major, 4–6 Pectoralis minor, 7 Coracobrachialis, 8 Supinator brevis, 9 Triceps longhead, 10 Brachialis, 11 Biceps longhead, 12 Triceps lateralis, 13 Pronator teres, 14 Biceps shorthead, 15 Triceps medialis, 16 Brachioradialis, 17 Anconeus, 18–21 Trapezius, 22–23 Rhomboid major, 24–26 Latissimus dorsi, 27–32 Serratus anterior, 33–35 Deltoid, 36 Supraspinatus, 37 Teres minor, 38 Infraspinatus, 39 Teres major, 40 Subscapularis.

- **ergonomics:** activation of the four main areas of the upper part of the human body: shoulder, chest, back and arm;
- **spatial information:** 3D trajectories of the involved movements, and arrows oriented according to their main directions.

This overview shows, on the one hand, the non-uniformity of the movement space, yet on the other hand, each cluster contains movements that share similarities regarding their spatial information and other attributes. This is important for their interpretation and their later use for guiding UI design.

This clustering confirms our results from the previous section. For example, we looked at the spatial distribution of the movements for the three deltoid muscles on the shoulder (Figure 7.2(a)). These movements are contained in clusters 6, 10, 11 and 7, which have a high shoulder activation. Furthermore, we examined the muscle activations for precise and non-precise movements (Figure 7.2(b)). We saw that in general the chest and shoulder muscles are more activated in the case of precise movements. This trend is also shown in Figure 7.8 where clusters with the highest precision (clusters 4, 9, 10 and 11) present a high activation in the same areas.

The total normalized muscle activations for each cluster are reported in Figure 7.9. Note the clear differences between the clusters, which serves as another indicator for a good clustering.

### 7.4.3 Description of Clusters

We make the following observations about each cluster:

**Cluster 1** covers short- and medium-length movements in the central and left upper parts of the space, directed diagonally closer to vertical. This cluster exhibits lower than average throughput of movements; in particular, a small advantage in speed is counterbalanced with twice-greater drawbacks in accuracy. Muscle activations are high for the infraspinatus and anterior deltoid, medium for medial deltoid, brachialis and biceps, and low for all other muscles. Movements in this cluster are suitable for short-term interaction, for alternation with other clusters, or in exergaming to train the anterior deltoid.

**Cluster 2** covers short- and medium-length movements in the lower right and central parts of the space in all directions, and some long vertical movements in the middle part of the space. This cluster has slightly

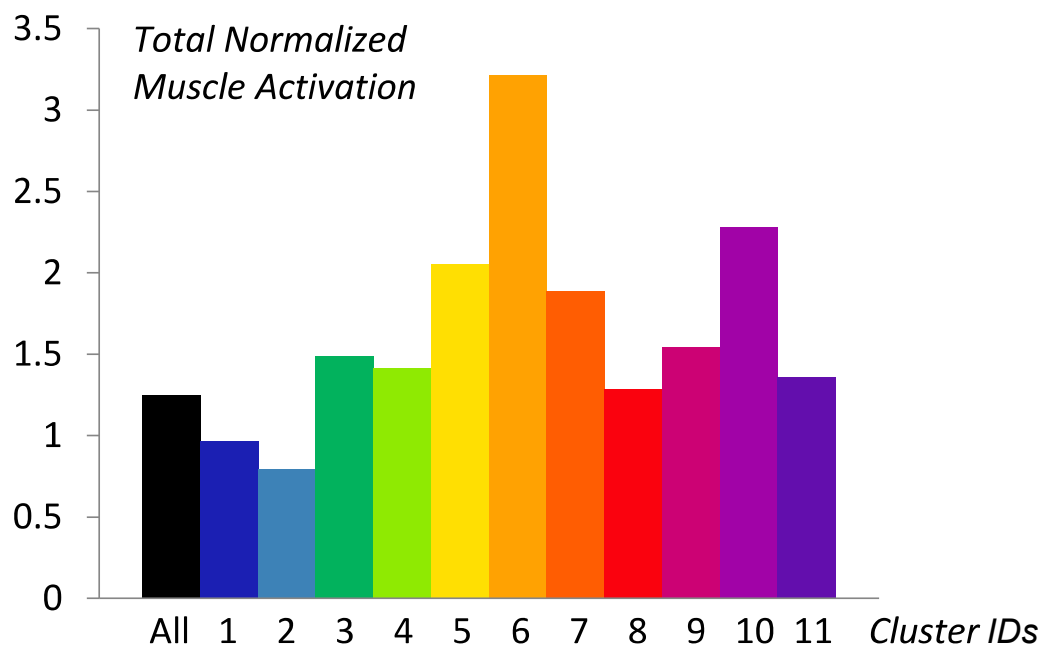


Fig. 7.9: Total normalized muscle activations for each cluster.

higher than average throughput of movements; improvements are present in both accuracy and speed. Muscle activations are high only for the medial deltoid, medium for anterior deltoid, brachialis, pronator teres and infraspinatus, and low for all other muscles. This cluster exhibits better than average performance and optimal energy expenditure, which makes it suitable for the majority of interfaces which need long-term interaction. Exergames within this cluster would not be effective.

**Cluster 3** covers long and medium-length movements in the central and upper part of the space, directed diagonally closer to horizontal. This cluster exhibits lower than average throughput of movements; in particular, a slight advantage in accuracy is counterbalanced by twice-greater drawbacks in speed. Muscle activations are high for the infraspinatus and anterior deltoid, medium for medial deltoid, supraspinatus, serratus anterior, brachialis, pronator teres, upper trapezius and rhomboid major, and low for all other muscles. Movements within this cluster can be used for short-term interaction with huge public displays, where large movements are necessary, or for sports exergames, for example tennis.

**Cluster 4** covers long close-to-vertical movements in the right upper part of the space, smoothly transitioning through close-to-diagonal movements in the lower right part of the space, to close-to-horizontal move-



ments in the lower left part of the space. This cluster has slightly lower than average throughput; in particular, an increase in accuracy is strongly counterbalanced by a decrease in speed. Muscle activations are high for the anterior and medial deltoids, infraspinatus and brachialis, medium for posterior deltoid, supraspinatus, triceps, pronator teres and part of the trapezius, and low for all other muscles. Movements within this cluster are close to the movements performed in sports, in tennis or golf. It can be used for exergames, for training.

**Cluster 5** covers short and medium-length horizontal movements in the left and central part of the space. This cluster has lower than average performance; the accuracy is 1.5 times lower than the speed is higher. Muscle activations are high for the anterior deltoid and infraspinatus, medium for brachialis, pronator teres and trapezius, and low for all other muscles. Movements in this cluster are suitable for low-accuracy interaction, for exergames, or primitive interactions with smartwatches.

**Cluster 6** covers short and medium diagonal close-to-horizontal movements in the topmost part of the space. The performance is a little bit higher than average; a small decrease in accuracy is compensated for by a twice-greater increase in speed. Muscle activations are high for all deltoids, supraspinatus, brachialis, trapezius and serratus anterior, medium for triceps, pronator teres, brachioradialis, rhomboid major and infraspinatus, and low for the rest of the muscles. Movements within this cluster can be used for training of multiple shoulder muscles.

**Cluster 7** covers medium-length and long movements between the leftmost lowest point and other parts of the space. This cluster has slightly higher than average performance, with better accuracy and lower speed. Muscle activations are high for the anterior deltoid, medium for other deltoids, teres minor, triceps, brachialis, brachioradialis, pronator teres, pectoralis major, serratus anterior, trapezius, rhomboid, infraspinatus and teres major, and low for a few other muscles. Movements within this cluster are the least convenient compared to other clusters, and their usage should be avoided.

**Cluster 8** covers long movements between opposite parts of the space. This cluster has 20% lower performance, reflecting both lower accuracy and much lower speed. Muscle activations are high for the anterior deltoid and infraspinatus, medium for brachialis and pronator teres and low for all other muscles. Movements within this cluster can be used for short interaction, alternation between types of load, or for exergames.



**Cluster 9** covers medium and long diagonal and close-to-horizontal movements mostly in the right and central parts of the space. This cluster has lower than average performance; in particular, accuracy is slightly higher and speed is almost twice as low. Muscle activations are high for the medial deltoid, medium for other deltoids, supraspinatus, infraspinatus and brachialis, and low for all other muscles. Movements within this cluster are suitable for short-term interaction, or for alternation between loaded muscles.

**Cluster 10** covers short and medium movements in the upper right part of the space in diagonal and mostly very close to vertical directions. This cluster has higher than average performance; both accuracy and speed are approximately 6% higher. Muscle activations are high for the posterior and medial deltoids, infraspinatus, upper trapezius and serratus anterior, medium for the anterior deltoid, and low for all other muscles. This cluster can be used for short-term interaction, for alternation and for interactions where high throughput is necessary.

**Cluster 11** covers short and medium mostly vertical movements in the right part of the space. This cluster exhibits higher than average performance; both accuracy and speed are 6% higher. Muscle activations are high for the medial deltoid, supraspinatus, upper trapezius and subscapularis, medium for serratus anterior, anterior and posterior deltoids and brachialis, and low for all other muscles. This cluster can be used for medium-term interaction or for alternation between muscle loads.

#### 7.4.4 Performance Analysis per Cluster

We computed Fitts' law models [8] for each cluster separately and compared fitness for a model computed for the whole dataset. We used the standard model introduced above, with  $a$  and  $b$  fit to subsets of movements defined by the clusters. As Figure 7.10 shows, the model fit per cluster is higher than for the whole dataset. The average model fit per cluster was  $R^2 = .97$ , whereas the fit for the whole dataset was  $R^2 = .95$ . This corroborates the plausibility of the clustering, as homogeneity of data within each cluster is higher than those of general dataset. The improvement of the model fit is not achievable through random re-clusterings. The models show up to 28% difference in throughput between the clusters. Details of the performance analysis of each particular cluster are given in Figure 7.10, as well as in the context of each cluster in Section 7.4.3.

## Overview of the Movement Space through Muscle Co-Activation Clustering

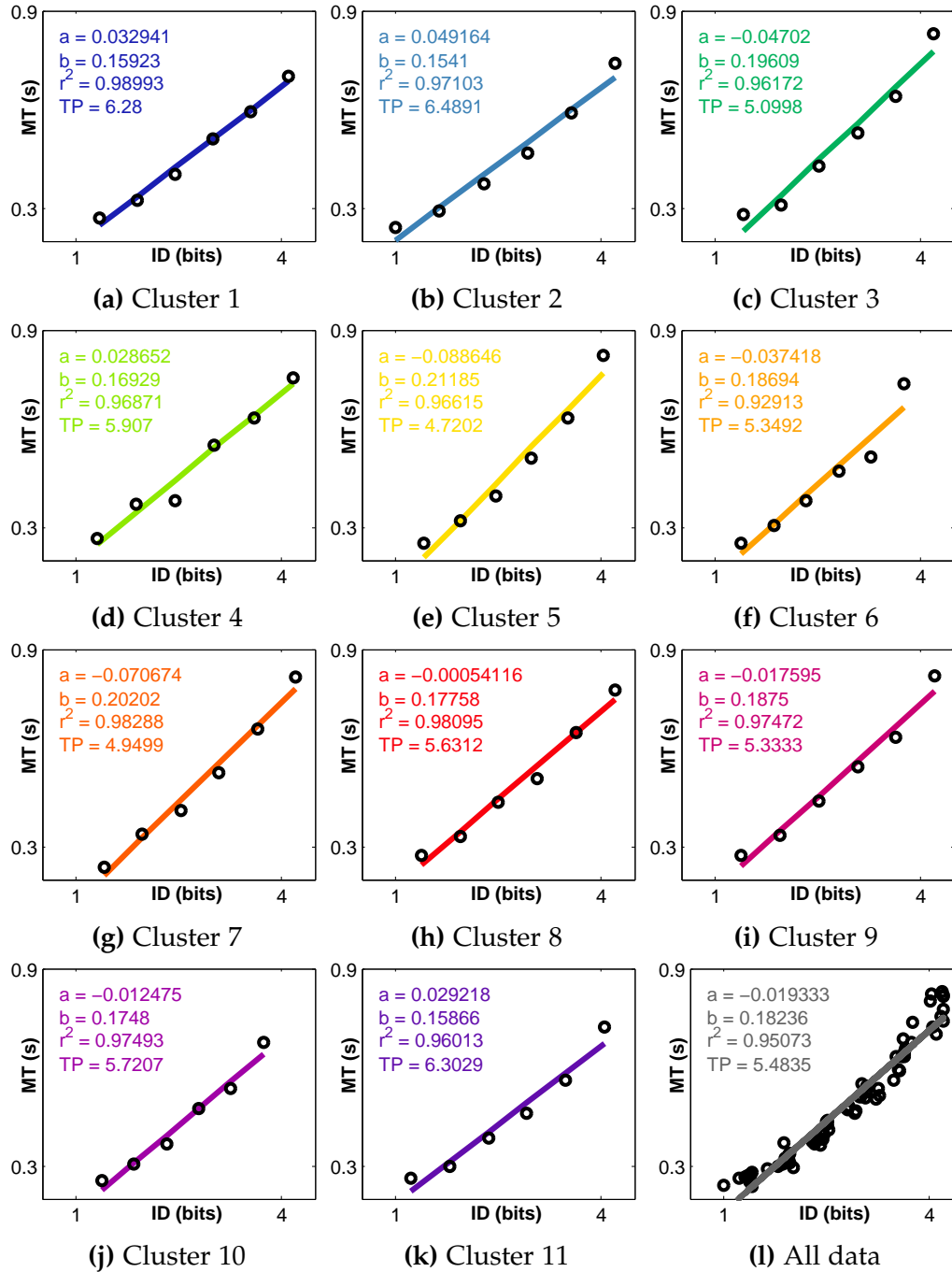


Fig. 7.10: Fitts' law models for the clusters show that improvements to fitness can be obtained by knowing the clusters.

## 7.5 Input Method Design

### 7.5.1 Application Algorithm

The typical approach to assessing the efficiency of input methods employs empirical studies. The proposed clustering allows any given *input region* to be examined for muscle load and user performance prior to such studies, or even instead of such studies. The clustering makes it possible to quickly quantify potential improvements and drawbacks when changing the interface from one cluster to another. While clustering is created based on mid-air aimed movement data, it also makes it possible to assess other types of devices which do not involve large external forces; for example, interactions with capacitive touch screens can be effectively evaluated by the method. The clustering can be applied in many scenarios by following this scheme:

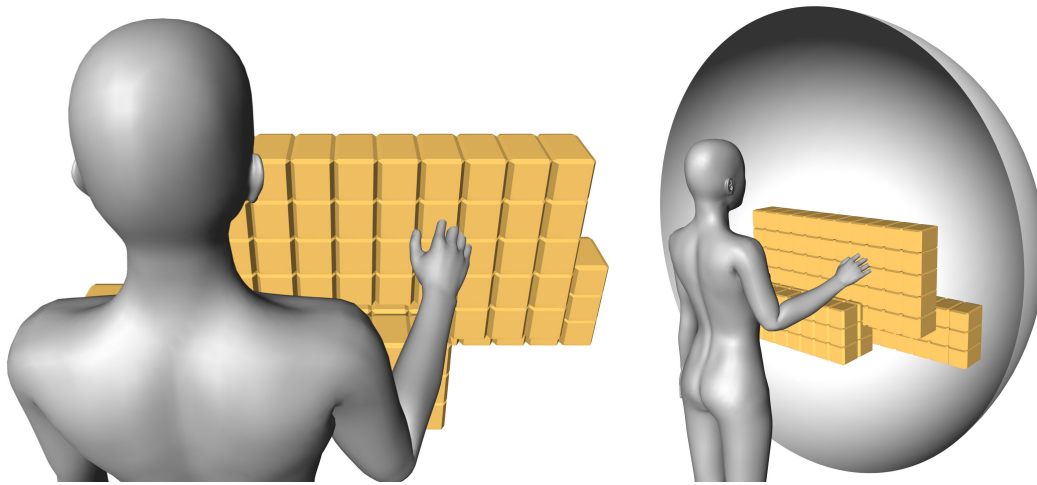
1. Identify characteristic properties of the involved movements: their length, their directions, and the 3D volume in which the movements are to be sensed.
2. Use Figure 7.8 and the corresponding descriptions from Section 7.4.3 to identify the clusters which strongly intersect that input volume.
3. Among these candidate clusters, find the ones which contain movements with the desired length and directions.
4. Finally, examine the performance and ergonomics properties of these clusters and choose the one which is most suitable for the application.

To illustrate some applications and evaluate our clustering, we consider three cases of UI design: 1) mid-air keyboard placement, 2) public display interaction, 3) mid-air input for a smartwatch.

As argued above, the clusters represent an upper bound on performance. The properties of the particular input method and the skills of the user are further aspects of the performance.

### 7.5.2 Case 1: Mid-Air Keyboard Placement

Our first example concerns design of a virtual keyboard for mid-air text entry by pointing with the arm (e.g., [157,386,387]). Such a keyboard is



**Fig. 7.11:** The optimal input region for a virtual keyboard lies within cluster 2 (see also Figure 7.8). This cluster has a good accuracy for aiming movements in a space that is large enough to host a virtual keyboard. Furthermore, the ergonomics in this cluster are very good: it has the lowest total normalized muscle activation (see also Figure 7.9).

already implemented in console games and remote controllers using IR cameras and accelerometer sensors, as well as using computer vision, as in Microsoft Kinect. These keyboards map the position of the arm end effector relative to a virtual cursor hovering over the keys, and selecting the keys is done using a separate command. In previous studies it has been researched how keyboard size or its depth influence the text entry. The question is, however, how these keyboards and individual keys should be mapped to human-centered 3D space to optimize for ergonomics and performance.

To answer this question, we search for clusters satisfying three constraints: first, the movements within the space need to be accurate enough to allow typing without typos; second, the space has to contain movement short enough to allow movements between individual keys; and third, the space should be large enough to allocate the whole keyboard. These constraints are satisfied in 4 clusters: 1, 2, 9 and 11. By examining Figure 7.8, we identify cluster 2 as providing satisfactory accuracy and the lowest total normalized muscle activations; thus, the optimal location for a virtual keyboard is in this cluster, as shown in Figure 7.11. As we can see, the resulting keyboard is positioned below shoulder level, horizontally centered in front of the shoulder, and covers volume in depth matching the length of the forearm.

### 7.5.3 Case 2: Public Display

Design of user interfaces is not only about some particular aspect, but concerns several of them, and while performance and ergonomics are the most important, there are in some cases other constraints.

For example, an interactive public display (Figure 7.12(a)) is mounted on a wall at a fixed height, and the user has to maintain a particular distance from it in order to be able to read it and have a full overview. The related movements are mostly 2-dimensional in the plane of the display surface and a small depth when moving from one target to another, as can be seen in Figure 7.12(b).

As we can see, in our example the menu is placed according to a desktop design recommendation at the top of the screen (Figure 7.12(b)), which visually can be identified as intersecting clusters 1 and 9. To check the actual cluster intersections, we have also computed a 3D representation of the menu movement space and immersed it in a virtual space of the recorded trajectories, which are shown in Figure 7.12(c).

From description of the clusters, we know that clusters 1 and 9 are not suitable for prolonged interaction, so placing the menu at the top of the screen will make users become fatigued too fast during menu navigation. Additionally, considering that our dataset represents an average adult male, such a menu could become an accessibility problem for shorter users, as in corresponding human-centered coordinates the menu would be out of reach.

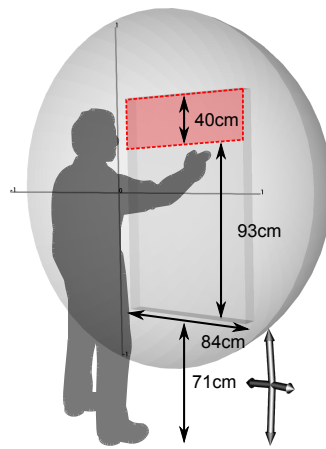
As an alternative menu location, we considered the space 30cm lower than initial menu (7.12(d)). It is completely contained in cluster 2, which is suitable for prolonged interaction. With this update the user performance would stay almost the same, but muscle activations are reduced by 2.7 times (7.12(e)).

### 7.5.4 Case 3: Smartwatch input

Our fourth case concerns the design of input for smartwatches [388]. The largest drawback of these devices is the very limited input space due to the small form-factor. The number of buttons on such a device is very small. Multitouch interfaces are not suitable, due to the tiny screen and the occlusions that would be caused by the hand. One of the alternatives for increasing the input space is to capture mid-air gestures using an integrated camera.



(a) Real-life example of a public display.



(b) Conceptual image showing size and position of the device in 3D space together with the main directions of the involved movements.

**% Movements:**

- Cluster 1: 23%
- Cluster 2: 9%
- Cluster 3: 8%
- Cluster 9: 53%
- Cluster 11: 7%

**Statistical results:**

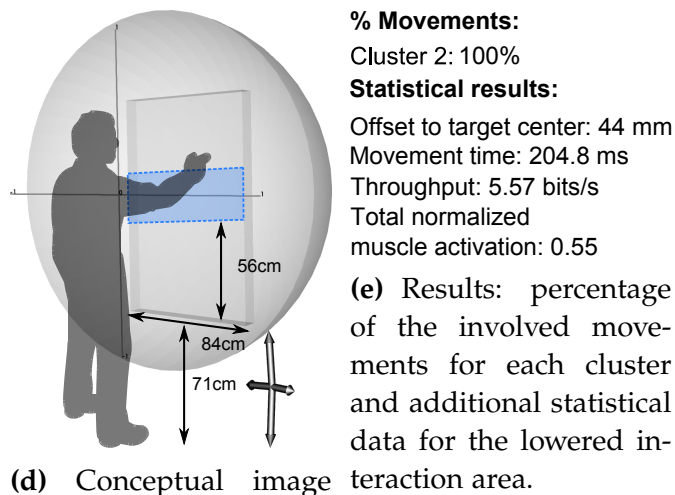
- Offset to target center: 48 mm
- Movement time: 449 ms
- Throughput: 5.52 bits/s
- Total normalized muscle activation: 1.5

(c) Results: percentage of the involved movements for each cluster and additional statistical data.

**Fig. 7.12:** Cluster-based design example: menu for interactive public display. We examined muscle load and user performance for the region on a vertical public display containing an interactive menu. Starting from a real-life example (a), we extracted its spatial setup and the main directions of its movements, (b). Using Figure 7.8 we identified the clusters that contain the desired movements: 1 and 9. These clusters are not suitable for long-term interaction.

We analyze here two options for camera placement for gestural interaction: the first option (Figure 7.13(a)) is used in the recently released *Samsung Gear*. The second option (Figure 7.13(d)) is our alternative to it, informed by our dataset and clustering.

The camera placement in Figure 7.13(a) requires the user to enter gestures with the right arm in the left contralateral area, namely in clusters 1 and 9. Our alternative design, on the other hand, features a camera facing to the right of the smartwatch, as demonstrated in Figure 7.13(d). This would allow interaction in Cluster 2, which is two times less fatiguing and provides higher accuracy and performance.



**(d)** Conceptual image showing a lowered interaction area.

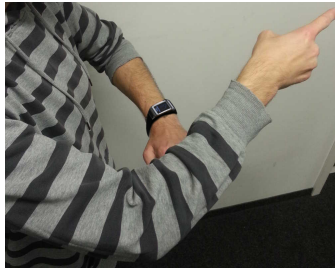
**Fig. 7.12:** (continued) Cluster-based design example: menu for interactive public display. Alternatively, we lowered the region in order to bring all movements to cluster 2 (*d*). As a result, the movements have better performance and lower ergonomic costs. More accurate cluster intersecting percentages and average performance and ergonomics values are shown in (*c*) and (*e*).

## 7.6 Discussion

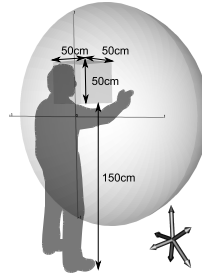
Motion capture-based biomechanical simulation is an efficient, effective and informative method for research and design on post-desktop interfaces. In this chapter we have presented an additional extension of the method to reduce the cost of its application for HCI tasks. Instead of running complete biomechanical simulation in the early stages of design, designers can get an overview of the movement space with respect to performance and ergonomics characteristics of different types of movements directly from a single scheme (Figure 7.8). The clustering provides mapping between various aspects of design and can be used in different ways: designers can specify a set of requirements predefined by a design (for example, movement locations, direction and amplitude, or speed, accuracy, throughput and muscle activations), get an overview of the rest of parameters within selected clusters, and select the optimal one for the specific task.

The clustering is based on an extension of a purely data-driven approach [353, 357, 358] in biomechanics of aimed movements uniformly





(a) Real-life example of a smartwatch. Interaction volume for the camera placement of Samsung Gear.



(b) Conceptual image showing size and position of the interaction volume in 3D space together with the main directions of the involved movements.

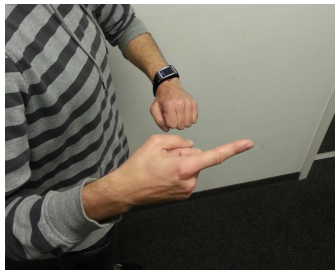
**% Movements:**

Cluster 1: 65%  
Cluster 9: 35%

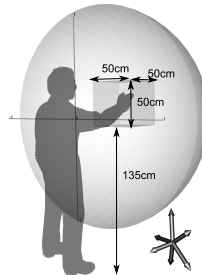
**Statistical results:**

Offset to target center: 59.8 mm  
Movement time: 404 ms  
Throughput: 4.7 bits/s  
Total normalized muscle activation: 1.7

(c) Results: percentage of the involved movements for each cluster and additional statistical data.



(d) Real-life example of a smartwatch. Interaction volume for an alternative camera placement.



(e) Conceptual image showing size and position of the interaction volume in 3D space together with the main directions of the involved movements.

**% Movements:**

Cluster 2: 100%

**Statistical results:**

Offset to target center: 60.8 mm  
Movement time: 442.5 ms  
Throughput: 5.9 bits/s  
Total normalized muscle activation: 0.8

(f) Results: percentage of the involved movements for each cluster and additional statistical data.

**Fig. 7.13:** We examined the muscle load and user performance for gestural input to a smartwatch. We considered 2 alternative interaction volumes depending on camera placement and direction (upper—Samsung Gear case, lower—alternative case). Starting from real-life examples (a, d), we extracted the spatial setup of the corresponding interaction volumes and the main directions of their movements (b, e). Using Figure 7.8, we identified the clusters that contain the desired movements: clusters 1 and 9 for the first case, and cluster 2 for the alternative case. More accurate cluster intersecting percentages and average performance and ergonomic values are shown in (c, f).



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covering the whole space reachable by the arm and coupled with performance metrics. The result is a summarization of muscle activation patterns of upper extremity muscles, which execute all movements covered in the dataset. Considering that the dataset uniformly and quite densely covers the movement space of the arm, it could describe well movements which are not present there. Surprisingly, the clusters computed on muscle activations are also prominent in the spatial domain, which is an additional confirmation of clustering validity and can be directly used by the designers. While looking at clusters in the spatial domain, it is possible to identify the movement parameters (location, direction) characterized by recruitment of the same group of muscles.

While this particular clustering can be used for analysis and design of interfaces involving mid-air arm movements, the approach is general and can be applied for other types of movement tasks in the following way:

- identify the movement space of interest,
- uniformly sample movements from this space using motion capture,
- simulate the underlying biomechanics and muscle recruitment,
- segment the whole recorded dataset based on muscle activation patterns,
- compute performance models for each class, and
- map the clusters back to the spatial domain.

In this way designers get an overview of the whole movement space and can make informed decisions concerning the desired interface, instead of guessing at design alternatives and evaluating them one by one.

To answer our **Research Questions 3.1 and 3.2**, we have shown that a complex movement space with 1800 different movements can be described in a set of only 11 equivalence classes. Each equivalence class contains movements homogeneous with respect to the recruitment of muscles which generate them, and all movements within a class are characterized by similar ergonomic and performance characteristics. With respect to performance, the clustering is a representation of a non-uniform movement space through a small set of uniform regions.



# Chapter 8

## Conclusions

### 8.1 Discussion

This thesis shows that biomechanical simulation, after a small set of adaptations, can be successfully applied to a wide range of HCI tasks, that it produces valid results, and that they provide new insights into performance and ergonomics of an input method. Additionally, the large movement space can be summarized in a small set of homogeneous regions based on the underlying physiology executing the movement, namely based on muscle activation patterns.

The proposed method effectively deals with the 4 issues of post-desktop user interface design.

First, the method is very efficient and generic with respect to user studies, and needs only slight overhead compared to a regular Fitts' law pointing experiment—5 minutes to calibrate the motion capture system and another 10-15 minutes to put on the MoCap suit, and adjust and calibrate markers. The motion capture system generally tracks movement of the body and end-effectors in 3D space and can be used for 3D, 2D and 1D pointing tasks, while most previous aimed movement studies were performed only in 1D or 2D and necessitated special hardware for each dimension setting, for example a regular mouse and display for 1D or 2D tasks, but a 3D mouse and volumetric display for 3D tasks. An additional advantage of motion capture in user studies is that it allows for tracking human movements as they are in a 3D and natural environment, without intermediary input devices or transfer functions, thus measuring pure human performance not affected by intermediaries. As modern motion capture systems provide sub-millimeter precision, they are suitable for most movement-based HCI tasks, excluding only the ones with

## Conclusions

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small movements and extra-high accuracy (higher than that of the mocap system) or force controls (for example isometric joysticks). Motion capture data also provides other advantages for performance analysis; for example, it could allow associating different performance fractions to individual limb segments.

Given such richness of motion capture data for performance analysis, the cost of physical ergonomics analysis comes only from the computational cost of biomechanical simulation, which is significantly lower than the cost of user studies. While regular biomechanical simulation involves tuning a lot of parameters for each individual subject and each movement, in Chapter 5 we have demonstrated that the simulation produces valid results even without fine-tuning, using a generic set of parameters for all participants and all movements. This makes the simulation even more resource-efficient for the HCI setting. The computational cost of current biomechanical software is still significant, but we know of current developments which accelerate the computation to real-time [389]. The biomechanical simulation outputs a wide range of physical ergonomics indices with high value to researchers and designers.

As a result, at a cost of a regular Fitts' pointing experiment, we get a rich dataset characterizing both performance and ergonomics of a particular set of movements. Considering the high efficiency of the method, it becomes possible to deal with the large movement space of post-desktop interfaces, either using biomechanical simulation in usability evaluations of design alternatives, or following our approach described in Chapter 7: uniformly covering the whole movement space in a user study, and summarizing it by a small set of homogeneous classes which can inform the design in early stages.

Second, having such an efficient method which deals with movements in 3D space and simultaneously provides both performance and ergonomics, it becomes possible to conduct more research on input methods beyond the desktop in more HCI laboratories. In particular, considering the lower cost of modern motion capture systems and biomechanical software, setups for motion capture-based biomechanical simulation will become accessible for almost every laboratory. The cost of equipment can be reduced even more with the development of markerless motion capture [276,368], or by deploying Microsoft Kinect for movement tracking (at the expense of accuracy). Furthermore, using our pipeline, these laboratories do not need high expertise in biomechanics or physiology to collect data and analyze input methods of interest.

Third, the non-uniformity of the movement space with respect to performance can be approached, as we described in Chapter 7, through association of movement performance to underlying biomechanical structures executing the movement. Of course, in our method we used hierarchical clustering and selected a small set of internally homogeneous clusters to keep the overview of movement space practical for designers, but in the real human body the number of homogeneous classes can be much higher, and the transition between classes can be smooth. We have demonstrated that such an approach is feasible and meaningful for whole-arm movements and 11 classes, but moving further in that direction, the movement performance can be associated with muscle synergies or even individual muscles.

Fourth, the physical ergonomics pitfalls can be approached using all biomechanical indices we get from the simulation. Different stages of simulation produce indices of different depth and focus in the human body: joint angles, joint moments, forces inside joints, muscle forces and activations. For each type of index, specific types of health risks can be considered. For example, for joint angles, risks are imposed by poses far from the neutral posture and close to joint limits; for forces inside joints and muscle forces, we can consider peak values as risk factors, as high peak force can damage joint ligaments, muscles or tendons; for muscle activations, we can consider the values integrated over the time of interaction as a measure of energy expenditure and muscular fatigue. Additionally, designers and researchers are free to define their own ergonomics indices which would, besides adhering to high-risk constraints, optimize for another measure, for example maximizing variability of postures or muscle recruitment to balance loads on individual muscles.

With respect to previous work on both performance and ergonomics, the proposed method is not only one of the most efficient and effective, but it is also the most generic.

With respect to performance, it is based on Fitts' law, but in contrast to it, the method tackles non-uniformity of the 3D movement space through movement equivalence classes. In this way the data within each class is more homogeneous and the fit ( $R^2$ ) of Fitts' models per class is improved over the general fit. The relation of performance to the underlying musculoskeletal system is similar to the kinematic theory, but unlike that theory our method does not assume separate functional muscle synergy for each individual movement, but uses muscle co-activation patterns prominent in the whole dataset. Such a representation is closer to physiologically-

## Conclusions

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based muscle synergies than to functional muscle synergies, and as a result it is more biologically plausible.

With respect to ergonomics, most previous methods deal only with one individual type of physiological index or load, and none of the methods encompasses such a broad range of variables as motion capture-based biomechanical simulation. The closest ancestors of our method—digital human models (DHM)—while providing joint angles and in some cases joint moments, do not provide any information on muscle forces or recruitment, or in the best case record it externally for preselected muscles using EMG. However, the benefit of some DHM is that they contain databases of human anthropometry and can predict static postures for different surroundings and tasks. In such cases, the user studies are skipped completely and indices of static postures are considered in design. Of course, such posture predicting functionality could be helpful extension for our method, in particular when applied for analysis of interaction with widgets fixed in the external world, one example of which is menu placement on an interactive public display. However, in post-desktop interaction we mostly consider dynamic movements, which cannot yet be predicted, so this is a promising future research direction.

In the context of the HCI field in general, this thesis contributes to the science and problem solving part of HCI by providing new methods and models, and less to the design part of HCI by providing recommendations, guidelines and examples. This thesis significantly increases problem-solving capacity [390], in particular for conceptual problems more important for the development of the field:

- The methodological contribution, namely the motion capture-based biomechanical simulation pipeline, allows other researchers as well as practitioners to efficiently tackle and make informed decisions about user performance and physical ergonomics of new user interfaces, in particular post-desktop input methods, using user studies which were not previously manageable. Additionally, the method provides deeper insight into each analyzed interface through a broad range of physical ergonomics and user performance indices. The significance of this contribution is high: the main stakeholders are the HCI researchers and practitioners performing user studies, but implications of the method application to actual design of post-desktop interfaces and consequent improvements can be reflected in large populations of users. For example, there are currently more

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than 1 billion smartphone users; furthermore, the costs of bad designs are even larger, as they include not only costs due to low interaction performance, failed technologies or devices, but significant risks to the health of the whole user population. The effectiveness is also relatively high, as the method provides rich data describing multiple performance and ergonomics aspects of interaction. Although the outputs do not include user experience, the above-mentioned factors are a prerequisite for it; namely, if performance or ergonomics are bad, user experience suffers as well. The efficiency of the method is high among HCI experiments, as it needs only slight overhead compared to a regular pointing task to capture movement dynamics and also generate ergonomics indices, although compared to model-based assessment the efficiency is much lower. Motion capture-based biomechanical simulation is transferable to a wide range of HCI tasks as already discussed, and has the potential to be applied for even more tasks with improvements in musculoskeletal models. Although relying on some assumptions and hypotheses (optimality of muscle recruitment), the method has demonstrated high validity and robustness with respect to individual simulation parameters, thus providing high confidence.

- The other methodological contribution, namely summarization of movement space through muscle co-activation clustering, allows researchers and practitioners to use the summary to inform their research or design. Additionally, although not providing an extensive motor control hypothesis, the clustering deals with some problems of the existing movement performance model—Fitts' law—by relating performance of a movement with underlying muscular groups executing it. In this way, Fitts' model parameters can be related to muscle groups, and considering a particular population can be used for forward performance predictions. The significance of this contribution is high, similarly to the previous one. The effectiveness is average, as it provides only a summary of the movement space with respect to performance and ergonomics and does not reflect all the details provided by the experimental pipeline. The efficiency of the contribution is high even among predictive models, as it quickly gives an overview over the whole movement space and can guide research or early stages of design. The transfer is also lower than for the experimental pipeline, as the current model covers only full-arm

mid-air movements. However, using the same approach, any movement space can be summarized and modeled, and in this way the transfer is high. The confidence of this contribution is high, albeit lower than that of the experiment pipeline, as it includes additional data-processing steps and is based on the assumption that the muscles are the base for a movement. However, behavior of the data in the clustering implicitly confirms the validity of the approach.

While it has been debated that the main reasons for fragmentation and problems in development of the HCI field is the lack of conceptual contributions [390] which would be able to bridge empirical and constructive contributions, the conceptual (methodological) contributions described in this thesis can fill this gap for physical ergonomics and performance of movement-based interfaces, and help to close the gap for predictive movement performance modeling in general.

As we can see, the motion capture-based biomechanical simulation could significantly improve post-desktop interface research and design. Besides some current limitations of the method, it can successfully tackle performance- and ergonomics-related design and research challenges in movement-based interaction. There were of course some critical questions on the applicability and validity of the method in HCI, as well as the value of the data, and we have answered these questions in the thesis.

To respond to **Research Question 1.1**, we have systematically analyzed related work in the relevant fields and as a result identified motion capture-based biomechanical simulation as a potential method for HCI research in Chapter 2. Further, we have proposed a small set of adaptations to the initial method to allow its application within HCI in Chapter 3. The proposed method is efficient, straightforward to apply and provides rich performance and ergonomics data, with only slight overhead compared to traditional HCI experiments.

To respond to **Research Question 1.2**, in Chapter 4 we performed the applicability user study collecting motion capture data of 5 different HCI tasks. Then we tried to run the simulation on all types of the recorded data, and noted failure cases and reasons for them. Although we analyzed only 5 types of interaction, it allowed us to identify strong and weak points of biomechanical simulation in HCI tasks. As a result, we have identified applicability limits and a range of potential successful applications. The method is applicable to all HCI tasks without subtle finger movements and without large external forces, for example for mid-



air interaction or touch interaction with capacitive sensors. Interactions involving external forces, such as button presses, external supports for body parts (armrests, seating), full-body (exergame) and dynamic (walking, running) interaction, or manipulations of physical objects (tangibles) necessitates recording of external forces. There is potential for improvement in finger simulations: first capturing hand movement with computer vision methods [368], and development in musculoskeletal hand models [391,392].

To respond to **Research Question 1.3**, in Chapter 5 we performed the validity user study collecting EMG and motion capture data for mid-air aimed movements. We compared muscle-related biomechanical simulation outputs against EMG recordings and found that the median correlation between the two is at 48% for a broad user population and an HCI setting. Additionally, we have found factors which influence validity and accuracy of the simulation: large muscles are better predicted than small ones; large fast movements are better predicted than slow and accurate ones; and the predictions are better for participants more closely matching the model representing an average adult male, but median correlations were positive even for young females. The participants representing population extremes with respect to body size, age, weight, or muscle state would necessitate manual skilled model adjustment to be valid. In the study we have validated the model for aimed movements, but considering that aimed movements are ubiquitous in HCI tasks and also provide a base for more complex behaviors [261], we can conclude that the method is valid for most HCI tasks.

To respond to **Research Question 2.1**, in Section 6.1 we conducted a user study of aimed movements in 6 touch device conditions. We found that movement performance significantly depends on the surface: the tabletop and smartphone 2-hands provide 30% higher performance than the tablet or laptop. Additionally, user performance depends on the posture used during interaction, reaching 7.4 bit/s for tabletop and 8.5 bit/s for smartphone 2-hands. Different throughputs provided on individual devices can be explained by different muscle groups executing movements in each posture.

To respond to **Research Question 2.2**, we continued the analysis of interaction with touch surfaces from Section 6.1 in Section 6.2 through deeper analysis of skeletal and muscular loads depending on touch surface and on posture. We have found that most users use an incorrect posture when interacting with a tablet, in which their neck loads are 5

times larger than normal. In general, public displays lead to the highest energy expenditure, and surprisingly, laptops induce the lowest energy expenditure, even slightly lower than tablets. Differences between individual postures are also large; for example, for tablets the energy expenditure ranges from 522 to 1561 units, with postures using external support for tablet having lower energy expenditure and postures better for neck demanding higher energy expenditure, particularly for arm muscles supporting the tablet at a higher position.

To respond to **Research Question 2.3**, in Section 6.1 we analyzed trade-offs between performance and ergonomics and found non-trivial relationships: in fact there was no trade-off, but rather a synergy between performance and ergonomics factors. Namely, bad ergonomics indices were related with low throughput movements, while high performance indices were related to better ergonomics indices, with long tails in both directions. Supposedly, this behavior is created by duration of movements: with longer durations the muscles need to resist gravity for longer periods and, consequently, fatigue more with respect to the same processed information bits.

To respond to **Research Question 3.1**, in Chapter 7 we performed clustering on muscle co-activation patterns of each movement within the space reachable by the arm collected in an extensive experiment. Similarly to the validity study, we used aimed movements, as they are ubiquitous in HCI and also serve as a base for all trajectory-based tasks [261]. Due to the size of the user study, we recruited a single participant—a well-balanced athlete—to represent skilled user performance, but his muscle recruitment patterns match those of regular users, as validated against samples of 16 other participants. We have found that it is possible to represent the large dataset through a small number of clusters which are interpretable in the spatial domain and exhibit more uniform performance and ergonomics properties within each cluster. The clusters can quickly provide a good overview of the movement space and inform the design of most mid-air input methods.

To respond to **Research Question 3.2**, in Chapter 7 we computed performance models for each cluster individually and for the whole dataset. We found that the fit of cluster-based models improved by 2%, which also confirms the validity of the clustering for the performance domain. In this way, the performance indices are related to the physiological bases underlying each movement, namely to corresponding muscle recruitment. This supports previous theories relating movement characteristics to the mus-

cle synergy properties responsible for the movement [261].

The chapters of the thesis provide answers to all our initial research questions, leading to the solution of the research problem:

**We can efficiently design, analyze and assess high-throughput ergonomic post-desktop input methods using motion capture-based biomechanical simulation as a source of data describing the interaction, and using summarizations or models derived from that data to inform the design.**

## 8.2 Future Research Directions

As biomechanical simulation is gaining new applications, more resources are being invested in this research direction. This results in rapid improvement of related technologies, and the biomechanical algorithms and models relevant for HCI will likely be improved as well. We have identified a number of problems of particular importance for HCI research, as described below.

### 8.2.1 Expanding Applicability Limits

As already mentioned, the main applicability limit of significant importance for HCI is fine finger movements. In order to enable finger simulation, the research should expand in two directions:

- First, a better kinematics tracking method is necessary for the hand and fingers. Current marker-based motion capture methods need overly cumbersome marker setups to accurately track all hand and finger segments. Additionally, hands are prone to significant amounts of self-occlusions, which would quickly degrade the quality of marker-based motion capture data. An alternative to this are cyber-gloves or markerless hand tracking methods [368]. Cyber-gloves are not the best option for HCI, as they impact the naturalness of movements, as well as prohibit capacitive touch and fine haptic feedback. Markerless hand tracking methods are the most promising direction, but currently they are not robust and accurate enough. Additionally, there will be a need to align and integrate markerless hand tracking with motion capture data of the rest of the body.

- A second direction is in the development of improved musculoskeletal hand models. Current hand models do not model factors important for capturing the complete richness of hand movements: internal palm joints, passive elastic tissue effects, intrinsic hand muscles and interconnected tendon networks inside the hand.

A second applicability limit is the presence of unmeasured external forces. There are two approaches to solve this:

- A first approach is development of cheap, easily attachable accurate 3D force sensors. There is significant progress in this direction, for example small 3D force sensors made from silicone, or force sensors integrated in shoes to measure ground reaction force.
- A second approach is to estimate them using some additional knowledge [393].

The external forces are important in multiple HCI tasks, for example tangibles, physical input artifacts and devices, body supports, etc.

### 8.2.2 Streamlining the method

To support practitioners in application of the method, it needs to be made more intuitive and simple to apply. While we have proposed an approach to streamline the method through a processing pipeline, there is still a lot of potential for improvement; for example, improvement of the user interface of biomechanical software would make it possible to more easily edit the models and make manual adaptations to them to match users. Another direction for simplification is deployment of full-body markerless motion capture [223], or even using Microsoft Kinect to track the kinematics. This would make it possible to use the method without the costs of a motion capture system, and without the overhead of marker setup. Additionally, it would allow participants to move freely without any restrictions. However, this simplicity comes at the cost of lower accuracy than provided by marker-based systems, so it is still necessary to investigate for which tasks the provided accuracy is sufficient.

### 8.2.3 Improving biomechanical simulation software

A significant practical issue of biomechanical simulation is the amount of time necessary for computations. For example, computations of inverse

kinematics, inverse dynamics and static optimization take 15, 50 and 1800 seconds for 240 frames of data; computed muscle control, while more accurate, is even slower [17]. Additionally, in current implementations the algorithms do not leverage benefits of multicore architectures. Faster simulation algorithms have already been proposed [389], but they are not applied anywhere yet, and additionally they will need to be validated for HCI.

### 8.2.4 Improving Validity of the Simulation

There are two issues with the validity of simulation:

- the current models employ many simplifications; for example, they represent many joints as hinges, and the segment inertia as that of a rigid body, and there are many muscular simplifications. Improving accuracy of the model would lead to more precise results, as well as to better predictions in close-to-extreme postures.
- current models represent an average adult male. However, for many tasks HCI deals with populations close to extremes with respect to size, weight or age. It is necessary to collect broader demographic statistics on each of the model parameters, and further applying such statistic-based model would make it easier to address the populations that are farther from average.

### 8.2.5 Developing a Predictive Model and Input Method Optimization

While we have shown that the complex biomechanical dataset can be summarized by a small set of equivalence classes, the further steps are to develop an analytical model representing the movement space. The model should be based on a plausible neuromuscular control hypothesis. Such a model would not only allow an overview of already recorded movements, but it would also be able to generate new types of movements not present in the dataset. Compared to clustering, such a model would have higher predictive power based on the same experimental data.

There are a number of recent projects which can provide a basis for development of such a model. One of the projects is a plugin which can help to develop neuromuscular simulations based on OpenSim [394]. Using this plugin, it becomes possible to integrate feedback control into

the biomechanical simulation, build Simulink models of neural control and computationally test motor control hypotheses.

Another direction for future research is model-based optimization of input methods and user interfaces. The described clustering can already be used for simple optimizations of an input method, as described in the case studies. However, analytical models of movements could open up the full potential for input method optimization. Additionally, further research is necessary to identify possible criteria for model-based input method optimization.

### 8.3 Concluding Remarks

This thesis proposes motion capture-based biomechanical simulation as an experimental method for efficient performance and ergonomics assessment of post-desktop input methods. The experimental procedure needs only slight overhead compared to common Fitts' law user studies: 10-15 minutes are necessary for putting on the suit with markers and calibrating the motion capture system. This method can be used within a UCD process to accelerate the assessment of design alternatives. Additionally, based on collected data, we propose a summarization of the movement space reachable by the arm with muscle co-activation clustering. This summarization can be used for a quick overview of the movement space to inform the design, or as a model-based performance and ergonomics assessment on early design stages.

Although there are still many open problems related to motion capture and biomechanical simulation within HCI, these methods can already be successfully applied to relevant problems.

# List of Figures

2.1	User-centered design process . . . . .	21
2.2	Collection of traditional input devices . . . . .	25
2.3	Direct measurement methods summary, informativeness vs. complexity . . . . .	39
2.4	Optical motion capture and external force recording during mid-air gestural interaction. . . . .	41
2.5	Electrode setup for EMG of 10 forearm muscles . . . . .	42
2.6	Respiratory measurement of walking . . . . .	44
2.7	Computed muscle control algorithm . . . . .	64
3.1	Terminology and setup for mocap data collection . . . . .	73
3.2	Biomechanical pipeline for HCI studies . . . . .	76
3.3	Interactive analysis tool MovExp with an application scenario . . . . .	81
4.1	Selected muscle activation predictions for three HCI tasks . . . . .	84
4.2	Self-made force platform to measure main components of external force. . . . .	85
5.1	Validation experimental setup and EMG electrode placement . . . . .	96
5.2	Examples of EMG vs. predicted muscle activation with high ( <i>left</i> ) and low ( <i>right</i> ) correlations. . . . .	98
5.3	Distributions of correlation coefficients between predicted muscle activations and EMG ( <i>left</i> ) and between prediction and subjective measures ( <i>right</i> ) . . . . .	99
5.4	<i>Top</i> : Correlations of muscle activation predictions with EMG recordings. Breakdown by muscle. <i>Bottom</i> : Breakdown by user. . . . .	100
6.1	Experimental setup and task for touch surface study . . . . .	106
6.2	Throughput and total muscle activation per surface type. Vertical bars denote confidence intervals. . . . .	111
6.3	Fitts' law models for each surface type. . . . .	114
6.4	Total integrated muscle activation vs. effective throughput. . . . .	115
6.5	Posture clusters (top) per surface. Total activations of major muscles are shown below per surface type. . . . .	116
6.6	The median postures for each surface type recorded in the study. . . . .	118
7.1	Experimental setup for mocap data collection covering the space reachable by the arm . . . . .	131

## List of Figures

---

7.2	Overview of the non-uniformity in the dataset. The three plots show how aimed movements in 3D space are non-uniform with respect to the recruitment of muscles for movements with different properties. Color saturation in (b) and (c) indicates the strength of the muscle activation. . . . .	134
7.3	Muscle activations of three different movements. A movement is characterized by the time-dependent activation of muscles (here: 41). The clustering is based on these muscle activations and assigns similar ones into the same cluster. . . . .	137
7.4	Quality measures for the clustering aid in selecting an appropriate number of clusters. . . . .	139
7.5	Dendrogram showing the hierarchical structure of the whole dataset. Red lines cut the dataset into clusters at the height selected by the goodness-of-clustering criteria; orange dashed lines correspond to the cuts performed manually. . . . .	140
7.6	Semantic representation of the dendrogram. The splits in this hierarchy are named after the muscle with the highest activation difference between the split sets. See the text for details about choosing the levels. . . . .	141
7.7	Description of manual splits in muscle co-activation clustering . . . . .	142
7.8	Each subfigure shows performance (barplots), ergonomics (LED visualization) and spatial information (3D trajectories and oriented arrows) for the final 11 clusters. The opacity of each LED is defined according to the average activation of the corresponding muscle in the current cluster. See the last part of this figure for the legend. (continued) . . . . .	143
7.8	(continued) . . . . .	144
7.8	(continued) The muscles represented in the LED visualization are: 1–3 Pectoralis major, 4–6 Pectoralis minor, 7 Coracobrachialis, 8 Supinator brevis, 9 Triceps longhead, 10 Brachialis, 11 Biceps longhead, 12 Triceps lateralis, 13 Pronator teres, 14 Biceps shorthead, 15 Triceps medialis, 16 Brachioradialis, 17 Anconeus, 18–21 Trapezius, 22–23 Rhomboid major, 24–26 Latissimus dorsi, 27–32 Serratus anterior, 33–35 Deltoid, 36 Supraspinatus, 37 Teres minor, 38 Infraspinatus, 39 Teres major, 40 Subscapularis. . . . .	145
7.9	Total normalized muscle activations for each cluster. . . . .	147
7.10	Fitts' law models for the clusters show that improvements to fitness can be obtained by knowing the clusters. . . . .	150
7.11	Cluster-based design: optimal placement of mid-air virtual keyboard . . . . .	152
7.12	Cluster-based design example: menu for an interactive public display . . . . .	154
7.12	(continued) Cluster-based design example: menu for an interactive public display . . . . .	155
7.13	Cluster-based design example: interaction volume for smartwatch mid-air gestures . . . . .	156



# List of Tables

2.1	Previous musculoskeletal models, their movement coverage and validity.	56
2.2	Comparison of biomechanical simulation against traditional instruments for physical ergonomics costs. . . . .	65
3.1	Output variables produced by the method. <i>Count</i> is based on simulations with the SIMM full body model. . . . .	75
4.1	Completion of simulation steps for five HCI tasks in the applicability study. See text for details. . . . .	87
5.1	Recommendations for improving accuracy of muscle activation prediction in HCI studies. . . . .	101
6.1	Dataset variables extracted by the different types of analyses. . . . .	112
6.2	The studied surface types. We introduce a color convention for the remaining analyses. . . . .	113
6.3	Performance and ergonomics indices for posture clusters. . . . .	119
6.4	Biomechanical indices for tablet interaction. . . . .	123
7.1	Description of all dataset variables . . . . .	135

## List of Tables

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