EG UK Computer Graphics & Visual Computing (2023)
D. Hunter and P. Vangorp (Editors)

Automatic balance assessment using smartphone and AI

M. Sganga[1,2,3], P. Rozmiarek[4], E. Ravera[5,6], O. Akanyeti [4] and F. Villagra Povina[3]

[1]Laboratorio de Investigación del Movimiento Humano, Universidad Maimónides, Argentina
[2]Departamento de ciencias de la salud, Universidad Nacional de La Matanza, Argentina
[3]Department of Life Science, Aberystwyth University, Wales
[4]Department of Computer Science, Aberystwyth University, Wales
[5]Group of Analysis, Modeling, Processing and Clinician Implementation of Biomechanical Signals and Systems, IBB, CONICET-UNER, Argentina.
[6]Human Movement Research Laboratory, School of Engineering, National University of Entre Ríos, Argentina

Abstract

Postural control assessment is essential for understanding human biomechanics in both static and dynamic situations. The relationship between the center of mass (CoM), center of pressure (CoP), and the base of support (BoS) determines whether a person is capable to maintain the balance. Inertial motion units (IMUs) are portable and cost-effective devices capable of measuring acceleration and angular velocity. The integration of IMUs into smartphones provides an accessible means of evaluating postural control in the general population without the need for expensive and time-consuming laboratory setups. A convolutional neural network (CNN) architecture will be employed to predict the difference between the CoM and CoP behavior during different tasks with data from an optoelectronic motion capture system combined with instrumented treadmill. This study aims to establish the foundation for developing an application that assesses postural control and balance in both healthy and pathological populations.

CCS Concepts

• ***Computing methodologies*** → *Artificial intelligence;* • ***Applied computing*** → *Life and medical sciences;* • ***>Human-centered computing*** → *Ubiquitous and mobile computing;*

1. Introduction

Postural control is a complex skill that depends on the dynamic interaction of musculoskeletal system and sensorimotor processes enabling individuals to engage in activities of daily living in a safe manner (standing, walking, etc.) [Hor06]. One of the goals of postural control is to maintain balance through postural equilibrium, which involves stabilizing the center of body mass (CoM) and the center of pressure (CoP, the centroid of ground reaction force exerted by the body on the floor) [Hor06]. During standing, the CoM and the CoP must remain within the base of support (BoS) [Win09]. During normal walking, the CoM and the CoP overpass the BoS, and dynamic stability can be preserved despite short periods in which the body is unsupported [JKC*04, Ric21, Kir06]. Therefore, achieving dynamic balance relies on the accurate coordination between CoM, CoP, and BoS. According to Morasso [Mor20] there are two distinct strategies to maintain balance: move the CoP to control the CoM or move the CoM to control the CoP. Both strategies involve relative displacement within the spatial domain.

Assessing postural control within clinical settings presents challenges due to multiple systems interacting with each other (somatosensory, vestibular, and visual systems). There is a range of validated observer-rated tests designed for different populations, such as patients with stroke [BBB*19, KAA*22, AAEAS18], Parkinson's disease [LCE11], cerebral palsy [SHRV13] and cerebral ataxia [WSH*15]. In laboratory settings, the gold standard for measuring kinematics and kinetics parameters is to use optoelectrical motion capture system (MoCap) and force plates [TR19, Ric21]. MoCap is an optical-based marker tracking and recording system for accurate motion capture in 3D space. The force plate technology is used to perform a precision measurement of ground reaction forces for biomechanical analysis and performance assessment. However, this evaluation is expensive, time-consuming, and constrained to the laboratory environment.

Advancements in wearable technologies have enabled the exploration of portable and accessible gait and balance measurements in more realistic scenarios. Recent research suggests that the future of biomechanical analysis should focus on the use of inertial motion sensor units (IMUs) with AI [UULD23, ea23]. Previous studies have demonstrated the advantages of employing multiple IMUs mounted on key body parts [RAW*20, RBW23], while others have explored the performance of a single IMU device [RvBBV20, LKP20, BET*20, RFB*22]. The integration of accelerometers and gyroscopes in smartphones has made it possible to assess a vast population. Several studies focused on developing mobile applications that run on standard mobile phones and

© 2023 The Authors.
Proceedings published by Eurographics - The European Association for Computer Graphics.
This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

DOI: 10.2312/cgvc.20231206

delivered by EUROGRAPHICS DIGITAL LIBRARY www.eg.org diglib.eg.org

measure gait and balance in healthy and pathological populations [AMA*20, APW*21, HCC*19, GMAC21, RBO*22]. However, to the best of the authors' knowledge, no research has yet investigated the inference of spatial displacement differences between the CoP and CoM using a single IMU from a smartphone. We hypothesize that the relative motion between CoP and CoM is a useful bio-marker to assess postural control and balance. Therefore, the main objective of this ongoing study is to develop a smartphone application that utilizes AI to infer the relative movement between CoP and CoM during quiet stance (when an individual is standing still) and gait in both normal and pathological populations. In pursuit of this objective, two secondary objectives will be addressed: 1) validating the application against the gold standard measure of motion capture (MoCap), and 2) validating the app against reliable clinical tests.

In this paper, we outline the experimental methodology for data collection and AI modeling toward achieving the project goals mentioned above.

2. Materials and methods

2.1. Participants and instruments

Data will be collected from both normal and pathological populations, with a target sample size of 40 subjects per group. The study will be approved by the NHS and Aberystwyth University Ethics Committee Boards, and all experiments will be conducted in accordance with the Declaration of Helsinki. All participants will give their informed consent before participating in the study. Three different technologies will be used: a smartphone, a MoCap system and an instrumented treadmill with force plates. The smartphone will be a Pixel 4a Google smartphone equipped with the AberStrokeApp application [SLD*21, SBA22] to collect three axes acceleration and angular velocity data with an acquisition frequency of 100Hz. A Vicon MoCap system consisting of six infrared cameras will be employed with a 100Hz frequency serving as the reference standard for determining CoM. An HP Cosmos treadmill instrumented with force plates with 1000Hz frequency will be used to measure CoP movements. Additionally, clinical tests will be administered to assess gait and balance performance.

2.2. Experimental procedure

Anthropometric measures will be taken (e.g., age, height, weight, ASIS width, and leg length). Each participant will have to perform several 2 different clinical tests: Berg Balance Scale (BBS) use to evaluate balance and functional mobility [PL17], and Dynamic Gait Index (DGI) use to to assess the ability to adapt and maintain balance during various gait tasks [JC07]. Then, the subjects will be instrumented with a sacroiliac belt modified to firmly house the smartphone over the lower back (around L5/S1). Over the smartphone 4 reflective markers will be placed to obtain kinematic data from the MoCap system. Additional markers will be placed on the anterior sacroiliac left and right spines to track the pelvis movement in the space. The participants will be asked to perform the static and dynamic tasks on the treadmill. The static task consists in standing as still as possible without arms movements in 2 different conditions: firm surface with open and closed eyes for up to 30 seconds. The dynamic tasks will evaluate the limits of stability in 4 different directions (move the CoP in different directions without falling, moving the arms, or altering the BoS), and walking at a fixed speed for 6 minutes. Data obtained from the force plates during different acquisitions are shown in 1 and 2.

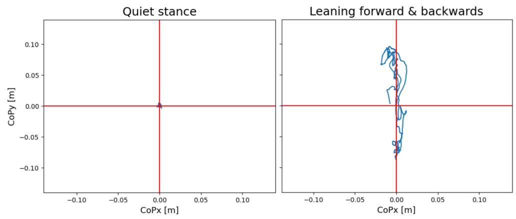

Figure 1: *CoP location during Quiet stance with eyes open (left) and evaluating the limits of stability in the forward and backward direction (right). xAxis: Lateral displacement [m], yAxis: Anterior-posterior displacement [m].*

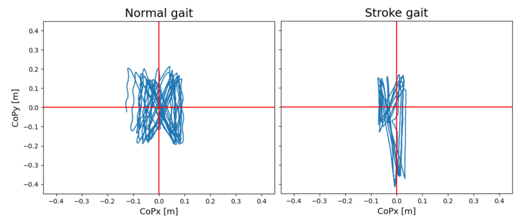

Figure 2: *CoP location during normal (left) and pathological (right) gait. xAxis: Lateral displacement [m], yAxis: Anterior-posterior displacement [m].*

2.3. AI architecture

All acquired data, including acceleration and angular velocity from the smartphone, and CoM and CoP (vertical axis = 0) movement from the motion capture (MoCap) system and treadmill, constitute time-series signals in three dimensions. In the post-processing stage, data from the smartphone will be synchronized with data from the MoCap system by computing the cross-correlation between these signals for all possible lags. The highest peak corresponds to the time difference between the signals, which enables the alignment of the signals.

Based on previous work [HKP*16, ZGJ*18, DNM*20], Convolutional Neural Networks (CNN) could prove to be a practical approach to mapping inertial sensor data of balance tasks and walking to CoM and CoP displacement. CNN models perform well on time-series spatial data analysis, making it suitable for this task. The type of layers will be analysed since different authors propose 1D [HKP*16, ZGJ*18] or 2D [DNM*20] convolutional layers to extract meaningful features from the input data. The number of layers will also be considered, Dorschky et al. [DNM*20] suggest that 2 layers perform better than 1 or 3 to avoid under or overfitting. We intend to train three CNNs. Each CNN will be trained on a distinct dataset comprising of pathological individuals, healthy individuals, and a combined dataset containing both groups. The subset models

© 2023 The Authors.
Proceedings published by Eurographics - The European Association for Computer Graphics.

can then be compared to the combined model allowing us to assess whether the relationship between CoM and CoP varies depending on the pathology. To optimize battery consumption and memory usage, we will try to identify a suitable subset of IMU signals for prediction purposes. This means using signals from just one of the two IMU sensors (accelerometer or gyroscope). We will then evaluate the performance of these models by measuring the error between the predicted and actual CoM and CoP values.

2.4. Conclusions

This is a work in progress towards developing a smart mobile application for automatic assessment of postural control that can be used in clinical environments to assist health care professionals while examining their patients. The paper outlines the experimental protocols for data collection and AI modelling, and presents preliminary data highlighting differences between normal and pathological balance control during standing and walking.

2.5. Acknowledgement

This work is supported by Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET, Argentina), Universidad Maimónides (UMai, Argentina), and Universidad Nacional de La Matanza (UNLaM, Argentina) which enabled M.S. to visit Aberystwyth University. This work is also supported by the European Commission (H2020-MSCA-RISE-2019, grant No. 873178) to O.A.

References

[AAEAS18] ALGHADIR A. H., AL-EISA E. S., ANWER S., SARKAR B.: Reliability, validity, and responsiveness of three scales for measuring balance in patients with chronic stroke. *BMC Neurology 18* (9 2018). 1

[AMA*20] ARCURIA G., MARCOTULLI C., AMUSO R., DATTILO G., GALASSO C., PIERELLI F., CASALI C.: Developing a smartphone application, triaxial accelerometer-based, to quantify static and dynamic balance deficits in patients with cerebellar ataxias. *Journal of Neurology 267* (3 2020), 625–639. 2

[APW*21] ABOU L., PETERS J., WONG E., AKERS R., DOSSOU M. S., SOSNOFF J. J., RICE L. A.: Gait and balance assessments using smartphone applications in parkinson's disease: a systematic review. *Journal of medical systems 45* (2021), 1–20. 2

[BBB*19] BLOEMENDAAL M. V., BOUT W., BUS S. A., NOLLET F., GEURTS A. C., BEELEN A.: Validity and reproducibility of the functional gait assessment in persons after stroke. *Clinical Rehabilitation 33* (1 2019), 94–103. 1

[BET*20] BRABANDERE A. D., EMMERZAAL J., TIMMERMANS A., JONKERS I., VANWANSEELE B., DAVIS J.: A machine learning approach to estimate hip and knee joint loading using a mobile phone-embedded imu. *Frontiers in Bioengineering and Biotechnology 8* (4 2020). 1

[DNM*20] DORSCHKY E., NITSCHKE M., MARTINDALE C. F., VAN DEN BOGERT A. J., KOELEWIJN A. D., ESKOFIER B. M.: Cnn-based estimation of sagittal plane walking and running biomechanics from measured and simulated inertial sensor data. *Frontiers in bioengineering and biotechnology 8* (2020), 604. 2

[ea23] ET AL M. E. M.-A.: Assessing real-world gait with digital technology? validation, insights and recommendations from the mobilise-d consortium. *Journal of NeuroEngineering and Rehabilitation 20* (6 2023), 78. 1

[GMAC21] GREENE B. R., MCMANUS K., ADER L. G. M., CAULFIELD B.: Unsupervised assessment of balance and falls risk using a smartphone and machine learning. *Sensors 21*, 14 (2021), 4770. 2

[HCC*19] HOU Y.-R., CHIU Y.-L., CHIANG S.-L., CHEN H.-Y., SUNG W.-H.: Development of a smartphone-based balance assessment system for subjects with stroke. *Sensors 20*, 1 (2019), 88. 2

[HKP*16] HANNINK J., KAUTZ T., PASLUOSTA C. F., GASSMANN K.-G., KLUCKEN J., ESKOFIER B. M.: Sensor-based gait parameter extraction with deep convolutional neural networks. *IEEE journal of biomedical and health informatics 21*, 1 (2016), 85–93. 2

[Hor06] HORAK F. B.: Postural orientation and equilibrium: What do we need to know about neural control of balance to prevent falls? vol. 35. 1

[JC07] JONSDOTTIR J., CATTANEO D.: Reliability and validity of the dynamic gait index in persons with chronic stroke. *Archives of physical medicine and rehabilitation 88*, 11 (2007), 1410–1415. 2

[JKC*04] JEKA J., KIEMEL T., CREATH R., HORAK F., PETERKA R.: Controlling human upright posture: velocity information is more accurate than position or acceleration. *Journal of neurophysiology 92*, 4 (2004), 2368–2379. 1

[KAA*22] KHAN F., ABUSHARHA S., ALFURAIDY A., NIMATALLAH K., ALMALKI R., BASAFFAR R., MIRDAD M., CHEVIDIKUNNAN M. F., BASUODAN R.: Prediction of factors affecting mobility in patients with stroke and finding the mediation effect of balance on mobility: A cross-sectional study. *International Journal of Environmental Research and Public Health 19* (12 2022). 1

[Kir06] KIRTLEY C.: *Clinical gait analysis: theory and practice*. Elsevier Health Sciences, 2006. 1

[LCE11] LEDDY A. L., CROWNER B. E., EARHART G. M.: Functional gait assessment and balance evaluation system test: reliability, validity, sensitivity, and specificity for identifying individuals with parkinson disease who fall. *Physical therapy 91*, 1 (2011), 102–113. 1

[LKP20] LIM H., KIM B., PARK S.: Prediction of lower limb kinetics and kinematics during walking by a single imu on the lower back using machine learning. *Sensors (Switzerland) 20* (1 2020). 1

[Mor20] MORASSO P.: Centre of pressure versus centre of mass stabilization strategies: The tightrope balancing case: Cop vs. com stabilization strategies. *Royal Society Open Science 7* (9 2020). 1

[PL17] PARK S.-H., LEE Y.-S.: The diagnostic accuracy of the berg balance scale in predicting falls. *Western journal of nursing research 39*, 11 (2017), 1502–1525. 2

[RAW*20] REVI D. A., ALVAREZ A. M., WALSH C. J., ROSSI S. M. D., AWAD L. N.: Indirect measurement of anterior-posterior ground reaction forces using a minimal set of wearable inertial sensors: From healthy to hemiparetic walking. *Journal of NeuroEngineering and Rehabilitation 17* (6 2020). 1

[RBO*22] RASHID U., BARBADO D., OLSEN S., ALDER G., ELVIRA J. L., LORD S., NIAZI I. K., TAYLOR D.: Validity and reliability of a smartphone app for gait and balance assessment. *Sensors 22* (1 2022). 2

[RBW23] RIEK P. M., BEST A. N., WU A. R.: Validation of inertial sensors to evaluate gait stability. *Sensors 23* (2 2023). 1

[RFB*22] RENTZ C., FAR M. S., BOLTES M., SCHNITZLER A., AMUNTS K., DUKART J., MINNEROP M.: System comparison for gait and balance monitoring used for the evaluation of a home-based training. *Sensors 22* (7 2022). 1

[Ric21] The assessment of center of mass and center of pressure during quiet stance: Current applications and future directions, 6 2021. 1

[RvBBV20] REFAI M. I. M., VAN BEIJNUM B. J. F., BUURKE J. H., VELTINK P. H.: Portable gait lab: Estimating over-ground 3d ground reaction forces using only a pelvis imu. *Sensors (Switzerland) 20* (11 2020), 1–12. 1

[SBA22] SHER A., BUNKER M. T., AKANYETI O.: Towards personalized environment-aware outdoor gait analysis using a smartphone. *Expert Systems* (2022), e13130. 2

© 2023 The Authors.

[SHRV13] SAETHER R., HELBOSTAD J. L., RIPHAGEN I. I., VIK T.: Clinical tools to assess balance in children and adults with cerebral palsy: a systematic review. *Developmental Medicine & Child Neurology 55*, 11 (2013), 988–999. 1

[SLD*21] SHER A., LANGFORD D., DOGGER E., MONAGHAN D., LUNN L. I., SCHROEDER M., HAMIDINEKOO A., ARKESTEIJN M., SHEN Q., ZWIGGELAAR R., ET AL.: Automatic gait analysis during steady and unsteady walking using a smartphone. 2

[TR19] TESIO L., ROTA V.: The motion of body center of mass during walking: a review oriented to clinical applications. *Frontiers in neurology 10* (2019), 999. 1

[UULD23] UHLRICH S. D., UCHIDA T. K., LEE M. R., DELP S. L.: Ten steps to becoming a musculoskeletal simulation expert: A half-century of progress and outlook for the future. *Journal of Biomechanics 154* (6 2023), 111623. 1

[Win09] WINTER D. A.: *Biomechanics and Motor Control of Human Movement*, vol. 2nd. 2009. 1

[WSH*15] WINSER S. J., SMITH C. M., HALE L. A., CLAYDON L. S., WHITNEY S. L., MEHTA P.: Systematic review of the psychometric properties of balance measures for cerebellar ataxia. *Clinical rehabilitation 29*, 1 (2015), 69–79. 1

[ZGJ*18] ZRENNER M., GRADL S., JENSEN U., ULLRICH M., ESKOFIER B. M.: Comparison of different algorithms for calculating velocity and stride length in running using inertial measurement units. *Sensors 18*, 12 (2018), 4194. 2

© 2023 The Authors.
Proceedings published by Eurographics - The European Association for Computer Graphics.