Eurographics Workshop on 3D Object Retrieval (2011)
H. Laga, T. Schreck, A. Ferreira, A. Godil, I. Pratikakis, and R. Veltkamp (Editors)

Heat diffusion approach for feature-based body scans analysis

C.Lovato[1] and C.Zancanaro[1] and U.Castellani[2] and A.Giachetti[2]

[1]Dipartimento Scienze Neurologiche, Neuropsicologiche, Morfologiche e Motorie, Università di Verona
[2]VIPS Lab., Dipartimento di Informatica, Università di Verona

Abstract

In this paper we propose the use of spectral shape analysis techniques for selection and classification of anthropometric points extracted from human-body scans. Few feature points are detected by exploiting the capability of heat diffusion process in capturing the extremities of surface protrusions which are often related to anthropometric landmarks. Then, a heat kernel signature is computed for each feature point which are associated to its semantic group by employing a learning-by-example procedure exploiting manual point labeling provided by an expert anthropometrist. Detected points are not clearly the same precise anatomical locations used in standard anthropometric procedures, but their matching can be useful for different applications like automatic model registration or simple body type evaluation. Experimental tests carried out on several subjects with different anthropometric characteristics show encouraging results demonstrating the potential usefulness of the approach as well as the necessity of further investigation on point description and matching.

Categories and Subject Descriptors (according to ACM CCS): I.3.5 [Computer Graphics]: Computational Geometry and Object Modeling—

1. Introduction

Anthropometric analysis of human scans is usually performed by employing device-specific and closed software solutions provided by scanner manufacturers, and requires often a careful acquisition, with strong constraints on subject pose. This may create problems in comparing data acquired in different places and performing large-scale multicentric studies as well as in applying advanced shape analysis tools on the captured models. The final goal of our work is to overcome these problems by selecting and customizing geometrical processing tools able to create an open and device-independent procedure for the analysis of body scanner data. To this aim, a feature-based approach is proposed in order to detect and classify *feature* or *salient* points which can be associated to anthropometric *landmarks*.

Feature-based approaches have recently become very popular in computer vision and image analysis application [Low04, MTS*05, MS05]. Using these approaches, an image is represented by a collection of local features. Two main steps are required: i) feature point detection, and ii) feature point description. Feature point detection aims at selecting a subset of interest points such as corner-like [MTS*05], or salient points [Low04]. Feature point description defines a compact representation of the point which enables its identification. In general a point descriptor is computed by collecting local characteristics in the point neighborhood. In shape analysis, feature-based approaches have been introduced more recently [BBB*10, ZBVH09, CCFM08, NN07] and are becoming a promising direction especially in shape retrieval applications [BBOGar, BBC*10]. In general, detected feature points are special points of the 3D surface which are characterized by some semantic or geometric properties. Typically, feature points are associated to interest parts of the shape such as anatomical parts (i.e., eyes, nose, fingers) or articulated junctions (i.e., for articulated objects). Feature point descriptors onto the 3D domain can be computed by considering either local properties of the shape or by exploiting the contribution of the whole model to the considered point. Desired properties of feature detectors and descriptors are the repeatability and robustness to different shape transformations [BBB*10].

Recently, effective 3D feature based techniques have been proposed by exploiting heat diffusion shape properties at different scales. In particular, the so called *Heat Kernel Signature* (HKS) has been introduced [SOG09] by showing effective performance for 3D shape matching [BBOGar,

DOI: 10.2312/3DOR/3DOR11/033-040

BBC*10]. The general idea consists of capturing information about the neighborhood of a point on a shape by recording the dissipation of heat from the point onto the rest of the shape over time. In this fashion, highly local shape characteristics are highlighted through the behavior of heat diffusion over short time. Conversely, more global shape properties are observed at longer time of heat diffusion. Such property of the heat kernel is useful for both feature points detection and description [SOG09, BBB*10].

In this paper we propose the application of heat diffusion techniques for the characterization of meaningful anthropometric landmarks in order to improve the automatic and computer assisted evaluation of anthropometric data obtained by a whole body scanner. The output of the scanner is a cloud of points, usually transformed in a triangulated mesh. Anthropometric landmarks are identified by our medical partner and correspond to semantic human body parts such as the head, feet, knees, nose, and so on. Several subjects have been analyzed with varying gender, size, weight and body-pose. It is worth noting that in order to address such variations the nice properties of the heat diffusion and the heat kernel signatures are crucial. In particular, the proposed procedure i) is stable under perturbation of the shape, that happen typically in different subjects, ii) it is invariant under isometric deformations, when the human body pose is changed, iii) it can be computed easily and efficiently.

The rest of the paper is organized as following: section 2 presents a concise overview of related geometrical processing methods that have been applied or can be applied to body scanner data, section 3 introduces the heat equation and the concept of heat kernel and in section 4 we show how we used it to detect and desctibe salient points in a mesh processing pipeline starting from data acquisition and ending with supervised labeling of the detected points. Section 5 presents experimental results obtained on a dataset of body shapes acquired during routinary anthropometric procedures.

2. Related work

In this section we review existing work on research themes related with this paper, e.g. automatic human body shape charcterization, feature-based shape analysis methods, and heat diffusion methods.

2.1. Automatic human body shape characterization

Recent advances on scanning techniques make possible to acquire high resolution models of the human body that can be extremely useful for anthropometric studies and for other applications like medical diagnosis, clothing design, computer animation and entertainment. Most of these applications could benefit of an automatic processing of the scanner data able to segment and recognize the different parts of the body and to locate reference points useful, for example, to perform anthropometric measurements. Although a huge literature is available on general shape segmentation [AKM*06, Sha08], not so many work deals with the reliable partitioning of a human body model into semantically consistent parts. A recent detailed review on scanned human body processing methods [Wer07b], presents and compare only few methods applied in literature to perform this task, most of them limited to standard postures, except for those developed by the authors, based on Reeb Graphs [XSW03, Wer07a]. Mortara et al. [MPS06] proposed the use of a surface point classification called *plumber* in order to identify tubular region and extract body parts, performing also anthropometric measurements. Yu et al. [YWXM07] proposed a method able to find automatically joints by computing specific measurements on volume sections. The method, however, requires a previous detection of body landmarks and limbs direction. In [LCG09] body partitioning is performed by extracting and segmenting the curve skeleton of the model. In this way it is possible to perform local measurements useful to locate landmarks or joints without slicing in pre-defined directions the surface.

It is worth noting that segmentation- and skeleton-based techniques are mainly useful to localize semantic regions of the body and their junctions. However, there are still several anthropometric landmarks that cannot be detected with those procedure. For instance, the fingers, the nose and the ears are well characterized landmarks which are not associated to a region but to a specific surface point or to a small area. For this reason in this paper we exploit feature based techniques to address this issues. Automatic body landmark recognition systems have been proposed in literature; an interesting work is presented, for example, in [BASM06] based, however on methods that are not scale and pose invariant. Recent research results demonstrated, however, the possibility of performing a robust and pose/scale invariant feature based shape analysis.

2.2. Feature-based shape analysis

Feature-based methods are composed of two main phases: i) feature points detection, and ii) feature point description. The detection step aims at selecting few and meaningful points from the entire object. The SIFT operator [Low04] represents the standard method on 2D domain, by allowing the detection of scale invariant feature points. Recently, such approach has been extended on 3D meshes [ZBVH09, NN07, CCFM08] by showing its robustness against noise and isometric variations. In [NN07] the authors proposed a surface flattening method in order to project the surface onto a 2D domain and apply the standard SIFT operator on it. In [ZBVH09, CCFM08] the proposed methods work directly onto the 3D domain by employing the so called Difference of Gaussian operator on 3D meshes [Low04]. Regarding feature point description the literature is larger and already consolidated also on the 3D shape domain [TV04, SF06]. Typically, local geometric surface properties are encoded as point descriptor such as surface normals, principal curvatures, shape index and so on [Pet02]. In [BBB*10] a recent comparison between different point detection and description methods is reported. It is interesting to observe that the most promising techniques are based on heat diffusion methods for both the phases.

2.3. Heat diffusion and shape analysis

Recently, new effective feature-based techniques have been proposed which employ heat diffusion methods on 3D shapes [SOG09, GBAL09, BBOGar, BK10, BBar]. In [SOG09] Sun et al. have proposed the so called *heat kernel signature*(HKS). The main idea is to describe the diffusion from a point to itself for several time instants. The HKS provides a natural and efficiently computable multi-scale way to capture information about neighborhoods of a given point. The authors shown the effectiveness of the HKS in distinguishing between different points of an object. Moreover, they shown that the local maxima of the heat kernel function at high scale are feature points. Similar approach has been proposed in [GBAL09] by introducing the so called *Auto Diffusion Function* (ADF). The idea and formulation is the same as in [SOG09] but the procedure is applied to object segmentation and skeleton extraction. In [BK10] a scale-invariant version of the heat kernel descriptor has been proposed. The framework is based on a logarithmically sampled scale-space in which shape scaling corresponds, up to a multiplicative constant, to a translation. The idea of the method is to undo this translation using the magnitude of the Fourier transform. The effectivess of the approach has been shown for shape retrieval. In particular, in order to represent the object as a collection of unordered feature points the Bag-of-Feature paradigm has been employed. The method has been further extended in [BBar] by applying the retrieval on large-scale database of shapes, namely *Shape Google*. The retrieval approach has been also improved by introducing spatial constraints on the signatures and by exploiting metric learning methods to improve the shape matching.

3. Heat diffusion process

Given a shape M as a compact Riemannian manifold, the heat diffusion on surfaces[†] is defined by the *heat equation*:

$$(\Delta_M + \frac{\partial}{\partial t})u = 0; \tag{1}$$

where u is the distribution of heat on the surface, Δ_M is the *Laplace-Beltrami* operator which for compact surfaces has discrete eigendecomposition of the form $\Delta_M = \lambda_i \phi_i$. In this fashion the *heat kernel* has the following eigendecomposition:

$$k_t(x,y) = \sum_{i=0}^{\infty} e^{-\lambda_i t} \phi_i(x)\phi_i(y), \tag{2}$$

where λ_i and ϕ_i are the i^{th} eigenvalue and the i^{th} eigenfunction of the Laplace-Beltrami operator, respectively. The heat kernel $k_t(x,y)$ is the solution of the heat equation with point heat source at x at time $t = 0$, i.e., the heat value at point y after time t. The heat kernel is *isometric invariant*, it is *informative*, *multi-scale*, and *stable* [SOG09, BBar]. Several stategies can be employed to estimate the Laplace-Beltrami operator on discrete meshes, in our experiments we used a discrete Finite Element Method [RBG*09].

4. Proposed method

Our idea is to investigate the possibility of automatically detecting meaningful anatomical landmarks and recognizing them using a supervised approach. To accomplish this task we developed a complete processing pipeline working on acquired body scanner data and consisting in a preliminary mesh processing, the application a salient point detector, the computation of point descriptors and the exploitation of the semantic labeling provided by an expert anthropometrist to perform point classification.

4.1. Pre-processing

3D models are arranged in form of triangular meshes that present various types of defects like holes, non manifold edges, bad shaped triangles and small unconnected regions, so a pre-processing step is mandatory. Pre processing is performed using MeshLab [CCC*08] in console mode, and consists of small components removal and Poisson remeshing creating a smooth and watertight triangulation with approximately the original resolution. In the final step the mesh is decimated, in order to obtain meshes with 15K vertices, used to perform the salient point detection and description. This size has been chosen taking into account the necessity of preserving the representation of main body anatomical structures, while keeping low the computational load of the subsequent spectral processing.

4.2. Feature-point detection

In order to detect a feature point we introduce the so called *autodiffusion* function as [GBAL09]:

$$ADF_t(x) = k_t(x,x). \tag{3}$$

The ADF describes the diffusion from the point x to itself. As highlighted in [SOG09] the local maxima of the ADF are feature points. In practice we detect a feature point x if $ADF_t(x) > ADF_t(x_i)$ for all x_i in the ring neighborhood of x. It is worth noting that at higher scales (i.e., large values of

[†] In this section we borrow the notation from [SOG09, BBar]

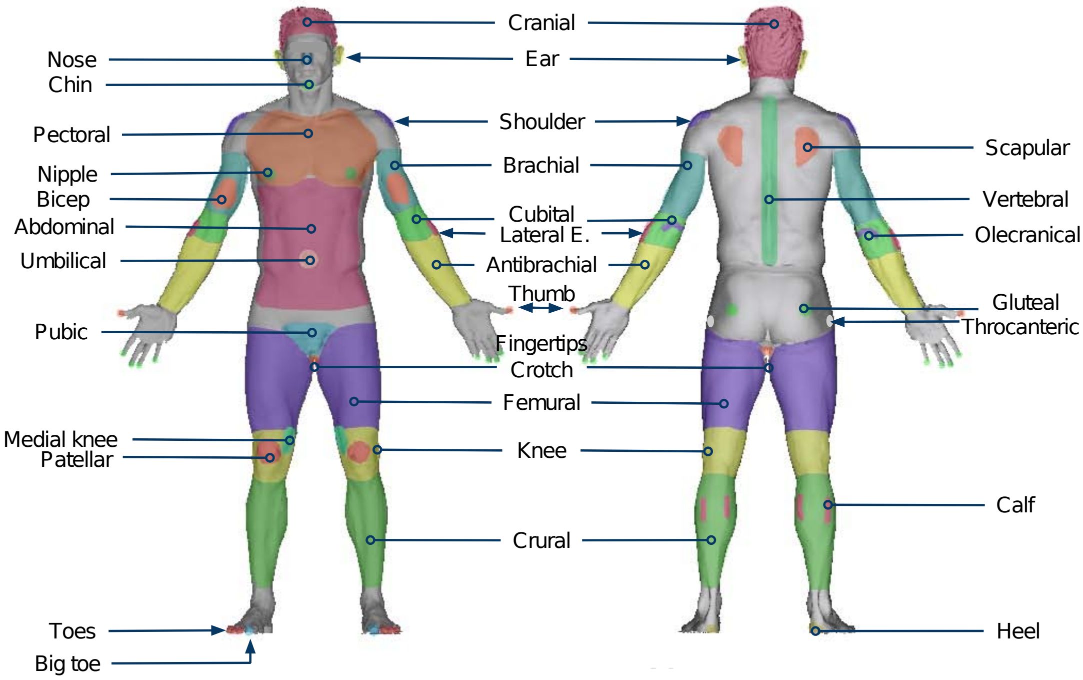

Figure 1: *Labels given by the expert. Some of them do not correspond to precise locations, but to extended regions where salient points are not evidently matching in different subjects.*

t) the detection selects only points with very strong protrusions. In order to increase the number of detected points we need to decrease t capturing more local surface features.

4.3. Feature-point description

In order to describe a feature point, we use the *Heat Kernel Signature* (HKS), introduced in [SOG09] and applied in [BBar] for object retrieval. Given a surface point x, the HKS is an n dimensional descriptor vector, defined as:

$$HKS(x) = [c(x)ADF_{t_0}(x), \cdots, c(x)ADF_{t_n}(x)]. \quad (4)$$

where $c(x)$ is selected in order to satisfy $||HKS(x)||_2 = 1$.

As suggested in [SOG09] we compute the HKS by uniformly sampling 100 points in the logarithmically scale over the time interval $|t_{min}, t_{max}|$, where $t_{min} = 4ln10/\lambda_{max}$ and $t_{max} = 4ln10/\lambda_2$. In practice the HKS signature is able to capture local shape properties at different scales. In the following, we will call s the integer variable corresponding to the HKS index: its values indicate specific scales that should correspond in different subjects. Obviously this is not exactly true due to variability in subjects' body types. This means, for example, that inter-subject HKS comparison performed by simply computing Euclidean distances in the samples space may not be the best way to match the relevant features characterizing the anatomical point. It may therefore be interesting to investigate also the use of alternative signatures derived by the heat kernel and/or the use of different metrics for their comparison. A possible derived descriptor can be obtained by observing that also the increments in switching from one scale to the next one have high discriminative properties. Therefore, as further descriptor we introduce the *derivative* HKS:

$$DHKS(x) = [c(x)DADF_0(x) \cdots, c(x)ADF_{n-1}(x)]. \quad (5)$$

where $DADF_i(x) = |ADF_{t_{i+1}}(x) - ADF_{t_i}(x)|$.

4.4. Feature-point classification

Given a set of automatically extracted salient points and a descriptor associated to each of them, we are interested in recognizing them assigning a semantic label, indpendently on pose, sex and body type. The idea is to use a supervised approach, asking to an expert anthropometrist to give labels to the detected points and then training classifiers using the extracted descriptors and the expert's labels.

The task is not, however, simple, due to the fact that, even if the HKS-based descriptor of a point should not depend on pose, it clearly varies with individual body features both local (affecting HKS at low t) and global, affecting HKS values at high t). This means that corresponding points are probably not concentrated in small regions of the feature space and that classes are not easily separable. For this reason the the most reasonable approach seem to use classifiers well adapted to examples of the different types, as, for example, K-Nearest Neighbor, and dissimilarity-based [PPD02]. The first assigns to the point the label most represented among closest example neighbors, accoding to a specified metric, while the second tries to classify points in the feature space created by the dissimilarity of the descriptors from a selected set of sample signatures extracted from training data. In Section 5 we present results of classification tests performed using the PRTools matlab toolkit [Dui00]. HKS and DHKS have been used as descriptors and K-NN and dissimilarity based classifiers have been applied.

Being the number of subjects in our database limited and the meshes' quality not very high, with topological variations making the recognition very hard, tests performed should be considered a preliminary work able to give useful hints for the future realization of an effective landmark recognition system.

5. Results

The dataset used in our experiments has been provided by the anthropometry laboratory of the Department of Neurological, Neuropsychological, Morphological and Movement Sciences of the University of Verona. The laboratory performs 3D body scanning during normal anthropometric routine using a structured light based body scanner device (Breuckmann BodyScan). This scanner creates high resolution (400k vertices, 1mm. resolution) meshes with an acquisition time of 5 seconds. The complete dataset consists of 40 human body meshes (20 young males, 12 young females and 8 obese women). On these models we performed the mesh processing pipeline described before, computing heat kernel values and detecting salient points at different scales.

We asked to an anthropometry expert to classify the points. He assigned to each detected point a semantic label that could be related to a precise anatomical landmark easily located and recognized in different subjects (e.g. nose, chin, heel), or to a body region if it could not be clearly recognized as anatomically meaningful location. The resulting classification procedure created 33 different labels for the detected points.

5.1. Feature-point detection

The number of features detected as heat kernel maxima is, as expected, higher, when the scale decreases (Fig. 2). Most of the feature points seems to be stable at different scales, moving from t_{max} $(s = 100)$ to t_{min} $(s = 1)$, so that, for decreasing s, the expert found that the previously extracted points were persisting (and were labeled accordingly) and new feature points appeared (and were labeled with new terms). In the following we

In Fig.3 we show the results obtained at different scales, in descending order. The bar graphs represent differently specific anthropometric points and regions where points can be grouped (outlined bars). At the coarsest scale $(s = 100)$ we have few regular points that can be easily recognized in all subjects as part of main anatomical structures. These results are similar on those presented in [SOG09]. Only the label 'other toes' is poorly represented due to the fact that toes are actually missing in the input decimated mesh. At finer scales, we can see that the features recognized at the maximum are still detected, and new features points appear (with an increasing rate for lower s), meaning that, for the regions where the landmark detection is poor, we could have a better detection using denser meshes and smaller t. At the finest scale of our analysis $(s = 1)$, however, most of the principal human body features are captured (see fig.), even if not all of them are detected for all the subjects tested (see Fig 3).

5.2. Feature-point classification

Not only the number of points detected and the percentage of successful detections, but also the recognition of these points depends critically on the scale (s) used for the detection. If we consider the detection at $t = t_{max}(s = 100)$, we have only three labels (collapsing toes labels into one) and the classification based on HKS is rather simple: classes are not linearly separable in the feature space, because the information at selected scale may be not discriminative, but with a simple non linear classifier like K-Nearest Neighbor, we obtained a 100% of correct labeling in leave-subject-out cross-validation test. This means that we can robustly recognize head, hands and feet on the acquired model.

If we want to capture more landmarks, we have to use a finer scale, and to check if a large number of detected points can be automatically recognized, we tested the HKS-based recognition using the points extracted at $t = t_{min}$. In this case, a leave-subject-out cross-validation test with a K-NN classifier trained with all the 33 different labels assigned,

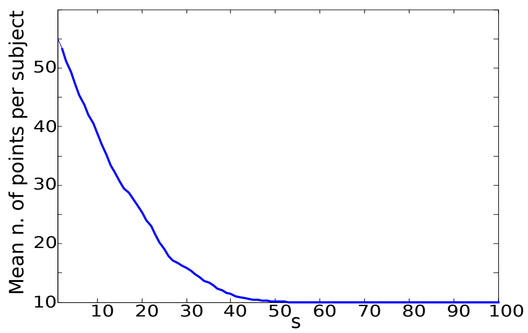

Figure 2: *The average number of points detected as heat kernel maxima on the test subjects is approximately constant at coarser scales and is continuously increasing at finer scales (lower s).*

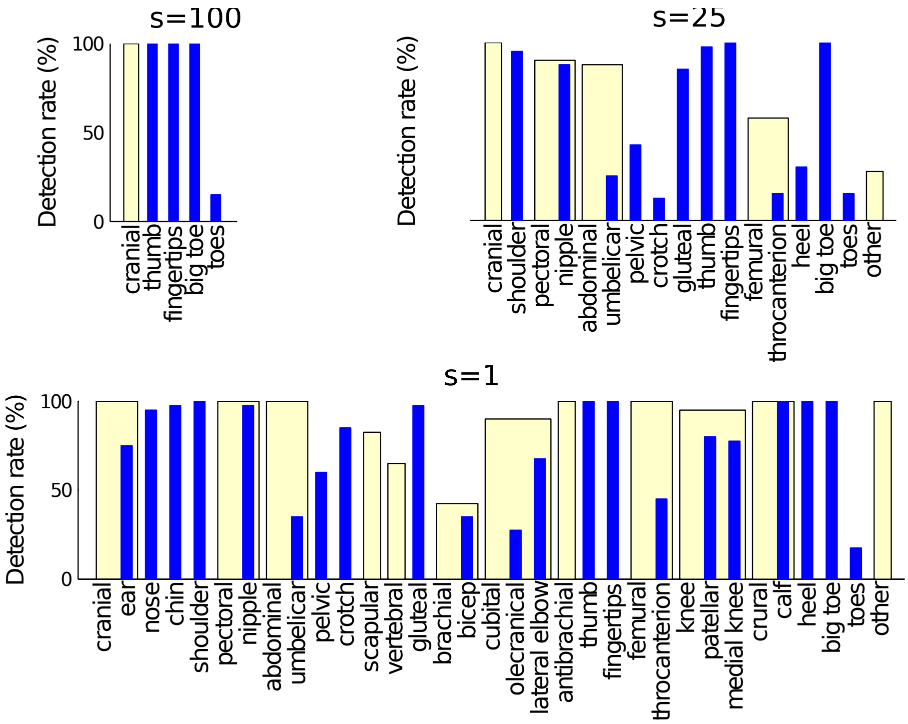

Figure 3: *Labeled points/regions detected at scale factors $s = 100$ (top left),$s = 25$ (top right), and $s = 1$ (bottom) with the corresponding rate of successful detections. At lower s values new point types appear, but the success rates in their detection is lower.*

provides a mean classification error not negligible (see Tab. 1). As written before, we tested different descriptors derived from the HKS and we found that the use of HKS derivatives (DHKS) with respect to the scale parameter t is more effective than the original HKS for landmark recognition (Tab. 1). We also implemented a dissimilarity-based classification procedure [PPD02], computing distances of original descriptors from a set of N examples and using them as the new feature vectors, generating the N-dimensional space where the labeling is performed. In this space, points with different true labels are more easily separated. In our experiments, for each classification test, we selected the salient points of five selected subjects (different from the tested one), computing the dissimilarity vectors for training and test points and training with them a Fisher classifier.

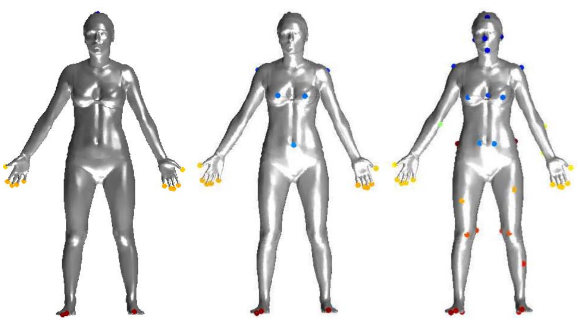

Figure 4: *Salient points extracted on one of the acquired models at $s = 100$ (left) $s = 25$ (center), $s = 1$ (right).*

Also in this case we completed in this way a leave-subject-out crossvalidation procedure obtaining average classification errors. Different metrics have been tested to compute the dissimilarity. The results included in Table 1 are those obtained with the distance measures giving the best results (chi square using HKS, angular distance using DHKS).

	KNN HKS	KNN DHKS	Diss.(chi sq.) HKS	Diss.(ang dist) DHKS
Avg. err.(33 lab.)	0.256	0.216	0.251	0.227
Avg. err.(24 lab)	0.211	0.171	0.164	0.153

Table 1: *Average classification errors obtained in leave-subject-out cross-validation tests on detected salient points with assigned original anatomical labels (33), and a derived labeling mixing close regions/points (24 labels). The use of DHKS reduces the error. The use of dissimilarity based classifiers also slightly increase the classification performances.*

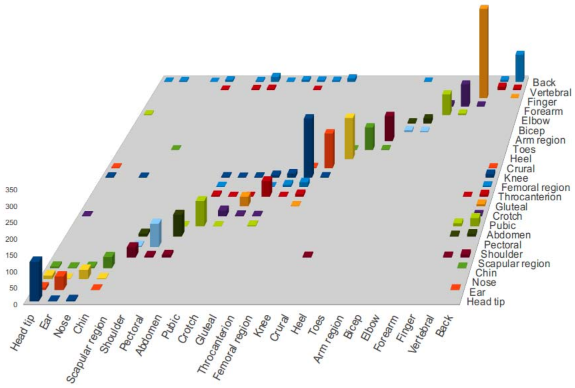

Figure 5: *Estimated vs. real labels on a leave-subject out cross-validation experiment using a simple KNN classifier and the original set of labels. Close points/regions are adjacent on the axes: errors are mainly due to mislabeling of close points or occur for particular labels that are assigned to large regions.*

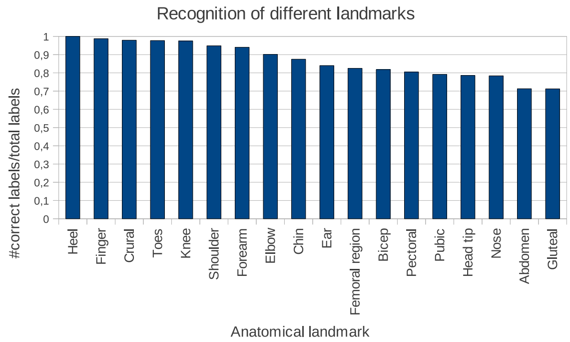

Figure 6: *Sensitivity, e.g. number of correctly labeled points over total number of corresponding labels for the different anatomical landmarks recognized by the expert.*

If we look at the confusion matrices (assigned labels versus true labels) obtained in our tests, we find that only particular classes of points are often misclassified, mainly due to the assignment of labels corresponding to adjacent points or regions.

This fact is clearly shown in Fig. 5 where the confusion matrix for the 33 labels K-NN classifier is represented, with salient points approximately ordered in a way to have close labels in the list corresponding to close points or regions. Errors are particularly relevant for labels that are assigned to large regions (e.g. vertebral, back). We tested also the classification results If we reduce the number of labels giving the same one to very close points or to points occurring in a labeled region and to the region itself, we have a classification problem with 24 labels and average classification error decreases to 15.3% with the best classifier tested (dissimilarity based on DHKS features).

What is more interesting, for us, is to analyze landmarks individually and see which are those that are well recognized with this method. Some of the points can, in fact, be recognized very well also with the generic signatures used in our tests. Figure 6 shows the sensitivity values for different landmarks obtained with the multi-class K-NN classifier trained with the reduced (24) label set and using 100 samples of the heat kernel derivatives as feature space (leave-subject-out cross-validation procedure). It is possible to see that the classifier has very good performances for selected features, that can be therefore recognized robustly even in the case of bad mesh quality (that was actually the case of our data set). These features (e.g. heel, crural, fingers, are also detected in all the models tested).

These results are clearly preliminary, they, however, indicate that the approach proposed is viable. We are going to perform more experiments on larger datasets, with improved mesh quality and more relevant pose variability. To increase the number of reliably recognized body points we plan to test also a single label classification approach with a specifically designed feature selection for each specific point and to introduce more specific context-aware features such as using diffusion distances from easily recognized points.

6. Conclusions

We presented a pipeline for the automatic detection and labeling of anatomical landmarks on 3D body scanner data based on the use of spectral shape analysis. Preliminary results shows that it is possible, using heat kernel maxima and heat kernel signature to detect and recognize robustly selected landmarks, while for other ones the recognition is not always good. Improvements in mesh resolution and quality and the use of different classification approaches with specific feature selection and further use of context information could probably result in better classification accuracy for these points.

We plan to do this as future work, as well as to test our approach on a wider set of data including meshes acquired by different scanners and more variable in pose.

Salient points labeled by the expert obviously do not correspond to the precise landmarks used in anthropometric procedures to evaluate sets of standard measurements, but are simply new automatically extracted locations corresponding to particular local and context-dependent surface features that can be found on all the scanned subjects and that are approximately independent on subject pose, sex and body type. These features can be useful for several applications, for example to automatically initialize the registration of articulated deformable models over the 3D data or the automatic estimation without manual intervention of simple body shape descriptors that can be better correlated with metabolic data than those commonly used (e.g. body mass index).

Furthermore, a robust recognition of the principal human body salient points can be effectively used as the first step of an hierarchical procedure able to precisely locate anthropometric points at a finer scale. We actually plan to implement a similar scheme as future work and to validate the results with manually extracted points typically used in anthropometric measurements.

References

[AKM*06] ATTENE M., KATZ S., MORTARA M., PATANE G., SPAGNUOLO M., TAL A.: Mesh segmentation - a comparative study. In *Proceedings of the IEEE International Conference on Shape Modeling and Applications* (2006), IEEE Computer Society, p. 7. 2

[BASM06] BEN AZOUZ Z., SHU C., MANTEL A.: Automatic locating of anthropometric landmarks on 3d human models. In *3DPVT '06: Proceedings of the Third International Symposium on 3D Data Processing, Visualization, and Transmission (3DPVT'06)* (Washington, DC, USA, 2006), IEEE Computer Society, pp. 750–757. 2

[BBB*10] BRONSTEIN A. M., BRONSTEIN M. M., BUSTOS B., CASTELLANI U., CRISTANI M., FALCIDIENO B., GUIBAS L. J., SIPIRAN I., KOKKINOS I., MURINO V., OVSJANIKOV M., PATANE G., SPAGNUOLO M., SUN J.: Shrec 2010: robust feature detection and description benchmark. In *Proc. EUROGRAPHICS Workshop on 3D Object Retrieval* (2010). 1, 2, 3

[BBC*10] BRONSTEIN A. M., BRONSTEIN M. M., CASTELLANI U., FALCIDIENO B., FUSIELLO A., GODIL A., GUIBAS L. J., KOKKINOS I., LIAN Z., OVSJANIKOV M., PATANE G., SPAGNUOLO M., TOLDO R.: Shrec 2010: robust large-scale shape retrieval benchmark. In *Proc. EUROGRAPHICS Workshop on 3D Object Retrieval* (2010). 1

[BBOGar] BRONSTEIN A. M., BRONSTEIN M. M., OVSJANIKOV M., GUIBAS L. J.: Shape Google: geometric words and expressions for invariant shape retrieval. *ACM Transaction on Graphics* (To appear.). 1, 3

[BBar] BRONSTEIN A. M., BRONSTEIN M. M.: Shape recognition with spectral distances. *IEEE Trans. Pattern Analysis and Machine Intelligence* (To appear.). 3, 4

[BK10] BRONSTEIN M. M., KOKKINOS I.: Scale-invariant heat kernel signatures for non-rigid shape recognition. In *Proc. Computer Vision and Pattern Recognition* (2010). 3

[CCC*08] CIGNONI P., CALLIERI M., CORSINI M., DELLEPIANE M., GANOVELLI F., RANZUGLIA G.: Meshlab: an open-source mesh processing tool. In *Sixth Eurographics Italian Chapter Conference* (2008), pp. 129–136. 3

[CCFM08] CASTELLANI U., CRISTANI M., FANTONI S., MURINO V.: Sparse points matching by combining 3D mesh saliency with statistical descriptors. *Computer Graphics Forum 27* (2008), 643–652. 1, 2

[Dui00] DUIN R. P. W.: Prtools - version 3.0 - a matlab toolbox for pattern recognition. In *Proc. of SPIE* (2000), p. 1331. 4

[GBAL09] GEBAL K., BAERENTZEN J. A., AANAES H., LARSEN R.: Shape analysis using the auto diffusion function. In *In SGP* (2009). 3

[LCG09] LOVATO C., CASTELLANI U., GIACHETTI A.: Automatic segmentation of scanned human body using curve skeleton analysis. In *Proceedings of Mirage* (2009), LNCS, pp. 34–45. 2

[Low04] LOWE D.: Distinctive image features from scale-invariant keypoints. *Int. Journal of Computer Vision 60*, 2 (2004), 91–110. 1, 2

[MPS06] MORTARA M., PATANÉ G., SPAGNUOLO M.: From geometric to semantic human body models. *Computers & Graphics* (2006), 185–196. 2

[MS05] MIKOLAJCZYK K., SCHMID C.: A performance evaluation of local descriptors. *IEEE Transactions on Pattern Analysis and Machine Intelligence 27* (2005), 1615–1630. 1

[MTS*05] MIKOLAJCZYK K., TUYTELAARS T., SCHMID C., ZISSERMAN A., MATAS J., SCHAFFALITZKY F., KADIR T., GOOL L. V.: A comparison of affine region detectors. *Int. J. Comput. Vision 65*, 1-2 (2005), 43–72. 1

[NN07] NOVATNACK J., NISHINO K.: Scale-dependent 3d geometric features. In *Int. Conf. on Computer Vision* (2007). 1, 2

[Pet02] PETITJEAN S.: A survey of methods for recovering quadrics in triangle meshes. *ACM Computing Surveys 34*, 2 (2002). 3

[PPD02] PEKALSKA E., PACLIK P., DUIN R. P. W.: A generalized kernel approach to dissimilarity-based classification. *J. Mach. Learn. Res. 2* (March 2002), 175–211. 4, 5

[RBG*09] REUTER M., BIASOTTI S., GIORGI D., PATANE G., SPAGNUOLO M.: Discrete Laplace-Beltrami operators for shape analysis and segmentation. *Computers & Graphics 33*, 3 (2009), 381–390. 3

[SF06] SHILANE P., FUNKHOUSER T.: Selecting distinctive 3D shape descriptors for similarity retrieval. In *International Conference on Shape Modelling and Applications* (2006), IEEE Computer Society. 2

[Sha08] SHAMIR A.: A survey on mesh segmentation techniques. *Computer Graphics Forum* (2008). 2

[SOG09] SUN J., OVSJANIKOV M., GUIBAS L.: A concise and provably informative multi-scale signature based on heat diffusion. In *Proceedings of the Symposium on Geometry Processing* (2009), pp. 1383–1392. 1, 2, 3, 4, 5

[TV04] TANGELDER J. W., VELTKAMP R. C.: A survey of content based 3d shape retrieval methods. In *International Conference on Shape Modelling and Applications* (2004), pp. 145–156. 2

[Wer07a] WERGHI N.: A robust approach for constructing a graph representation of articulated and tubular-like objects from 3d scattered data. *Patt. Rec. Letters 27* (2007), 643–651. 2

[Wer07b] WERGHI N.: Segmentation and modeling of full human body shape from 3-d scan data: A survey. *IEEE Transactions on Systems, Man, and Cybernetics, C 37*, 6 (2007), 1122–1136. 2

[XSW03] XIAO Y., SIEBERT P., WERGHI N.: A discrete reeb graph approach for the segmentation of human body scans. In *3-D Digital Imaging and Modeling, 2003. 3DIM 2003. Proceedings. Fourth International Conference on* (2003), pp. 378–385. 2

[YWXM07] YU Y., WANG Z., XIA S., MAO T.: Automatic joints extraction of scanned human body. In *HCI (12)* (2007), pp. 286–293. 2

[ZBVH09] ZAHARESCU A., BOYER E., VARANASI K., HORAUD R.: Surface feature detection and description with applications to mesh matching. In *Computer Vision and Pattern Recognition* (2009). 1, 2