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3D Description of the Human Body Shape Using Karhunen-Loève Expansion

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Abstract

The Karhunen-Loève expansion is used for a compact 3D description of the human body shape. In this paper we show that a compact 3D description can be achieved using a small set of eigenvectors. Experimental results using a database of three-dimensional body scans are presented. Applications are also discussed.

1.Introduction

The measurement of the human body (Anthropometry) is an essential part of the engineering design of cars, aircraft, workspaces, and clothing, to name a few. Traditionally such measurements involve the linear distances between anatomic landmarks and the circumferential values at predefined locations. Practically, such measurements are limited to a set of about 100 values.

There are, however, problems inherent with the use of traditional anthropometry as outlined in Robinette et. al [1]. First, the set of collected values is so small that the only valid attempt to reconstruct the original shape is limited to very simple geometries. Moreover, in most cases the set of unconnected (unregistered) values does not provide an accurate reconstruction of the original subject. Reconstruction ambiguities are due to the lack of a coordinate reference system. Furthermore, there can be large differences in measurement values between observers who collect the data even if they use the same measurement protocol.

Full body 3D digitizing, a recently developed technology as outlined in Robinette et. al [1], allows one to increase the number of measurements from a hundred to a million, in ten's of seconds and thus provides a better description of the human body surface. Furthermore each value in the data set is related to a common coordinate system, allowing an accurate and detailed 3D reconstruction.

CAESAR project (Civilian American and European Surface Anthropometry Resource) as outlined in Robinette et al [2], is the first three-dimensional surface anthropometry survey performed in both U.S. and Europe. During this project, body measurements have been taken for people between the ages of 18 and 65 in three countries: U.S, Netherlands, and Italy. Besides traditional measurement, full body 3-D scans have been recorded in three postures as shown in figure 1.

Two scanners were used to record full body 3-D scans: a Cyberware WB4 scanner[3] in the United States and Italy, and a Vitronic scanner [4] in the Netherlands.

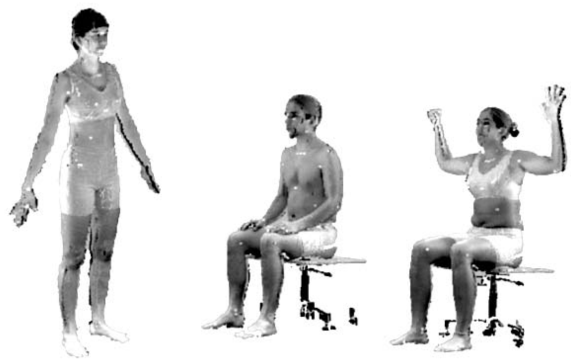

Figure 1. The three CAESAR postures

The CAESAR project is a collaborative effort with partners from several countries such as the Air Force Research Laboratory (AFRL) in Ohio, the Society of Automotive Engineers (SAE), the Netherlands Organization of the Applied Scientific Research (TNO) and the National Research Council of Canada (NRC).

After collecting a large number a body scans, the challenge is to analyze the human body shape variability using the provided 3-D database in order to improve the sizing strategy in the design of many products. To achieve this goal, a compact description of the human body shape is required. Even though a 3D scan provides a good description of the body surface, it represents a large amount of data (thousands of polygons), which is not convenient to study the variability of the human body shape. The description should also provide a faithful reconstruction of the original shape; otherwise it will not be more valuable than traditional measurements. This paper proposes a technique to achieve this goal.

Among the methods proposed in the literature of 3-D objects modeling, three-dimensional implicit functions such as algebraic functions, superquadricss and hyperquadrics provide a compact description.
Algebraic functions used by Sullivan et. al [5] and Keren et. al [6] require high order terms and several constraints to represent significant shapes. Superquadrics introduced by Pentland [7] and modified by Barr [8] and Solina et. al [9] are a family of parametric shapes which are extensions of ellipsoids. Hyperquadrics proposed by Hanson [10], are volumetric shape representation. Even though they have more representation power than superquadrics, hyperquadrics have a difficulty in representing objects with concavities. Ohushi et.al [11] developed the extended hyperquadrics to overcome this problem. However it has been demonstrated that the presented implicit functions are not adequate to represent complex objects such as the human body.

In the approach presented in this paper we consider the fact that the analyzed 3D objects belongs to the same family. Intuitively we can think that the family is low dimensional. It follows that any member might be represented by a small number of parameters. The Karhunen-Loève expansion, as outlined in Fukanaga [12], is used to extract a small subset of shapes, which allow the reconstruction of any of the shapes contained in the space spanned by this subset. The basic approach is similar to the one used in face recognition as outlined in Kirby et. al[13]. The data set considered here is three-dimensional body scans and the extracted shapes will be named “eigen-persons“ equivalently to the “eigenfaces” defined in face recognition experiments.

2.Method

2.1 Data pre-processing

For the purpose of this work we assume that the height of the human body is uncorrelated with its shape. In other words a short person and a tall person could have the same shape even though they don’t have the same height.
Although within the traditional anthro-pometric studies, the human height is a measure that has been largely investigated, the description of the human shape is still a challenge. That is why in this work we eliminated the variability related to the height by normalizing the height of all the persons in the database.

Before the normalization though, it is important to align all the persons in order to have a common center of gravity. After alignment and normalization, the variability in the 3D data corresponds only to the variability of shape.

We adopted a voxel description of the 3D data. In this case a cube of 1m of dimensions has been sampled to n voxels, where $n = (200)^3$. A function describing the occupancy of those voxels is equal to one if the voxel contains at least one point, and zero otherwise.

2.2. Karhunen-Loève expansion

We consider the use of the Karhunen-Loève expansion, also known as Principal Component Analysis (PCA) as outlined in Lebart et al [14]. The main idea of the approach is to find a set of vectors which best account for the distribution of the body shape within the entire shape space.

Each 3D person is converted into a vector form $\vec{\Psi}_i$ describing the occupancy of the n voxels. The mean person over a set of N persons is given by:

$$\overline{\Psi} = \frac{1}{N}\sum_{i=1}^{N}\vec{\Psi}_i \qquad (2.1)$$

Deviation vectors $\vec{\Phi}_i$ are generated and arranged in a data set matrix A as follows:

$$\vec{\Phi}_i = \vec{\Psi}_i - \overline{\Psi} \qquad (2.2)$$

$$A = \left[\vec{\Phi}_1\ \vec{\Phi}_2 \ldots\ldots\ldots \vec{\Phi}_N\right] \qquad (2.3)$$

The eigenvectors of the covariance matrix *C* defined as :

$$C = A^T A \qquad (2.4)$$

form the orthonormal basis that optimally spans the subspace of the human shape.
The eigenvectors, and their corresponding eigenvalues, of this $n \times n$ symmetric matrix *C* are ranked such that $(\lambda_i > \lambda_j)$ for $(i < j)$.

The magnitude of λ_j is equal to the variance in the data set spanned by its corresponding eigenvector $\vec{u}_j$ and is given by:

$$\lambda_j = \sigma_j^2 = \frac{1}{N}\sum_{i=1}^{N} \vec{\Phi}_i . \vec{u}_j \qquad (2.5)$$

It then follows that any vector $\vec{\Phi}_i$ in the data set, A, can be optimally approximated by:

$$\vec{\Phi}_i \approx \sum_{j=1}^{M} c_{ij}\, \vec{u}_j \quad 0 \le M \le n \qquad (2.6)$$

Thus, the *n*-dimensional body shape deviation vector can be re-defined as a linear combination of eigenvectors determined by *M* coefficients denoted by c_{ij} given by:

$$c_{ij} = \vec{\Phi}_i . \vec{u}_j \qquad (2.7)$$

Computing the 200^3 eigenvectors and eigenvalues of C is however impractical. Determining the eigenvectors $\vec{u}_i'$ and eigenvalues λ_j' of the $N \times N$ matrix given by

$$C' = AA^T \qquad (2.8)$$

represents a computationally feasible alternative to resolve the problem.

In fact, since the number of persons is less than the number of voxels ($N < n$), there will be only N meaningful eigenvectors rather than n. Moreover, the first *N* eigenvalues and eigenvectors of C are directly computed as follows:

$$\lambda_i = \lambda_i' \ \forall\, i \in [0, N-1] \qquad (2.9)$$

$$\vec{u}_i = \frac{1}{\sqrt{\lambda_i}} A\, \vec{u}_i' \ \forall\, i \in [0, N-1] \qquad (2.10)$$

The quality of the reconstruction is dependant on the fraction of the total variance contained in the M eigenvectors used in the reconstruction. This fraction q_M is given by:

$$q_M = \sum_{i=1}^{M} \lambda_i \Big/ \sum_{i=1}^{N} \lambda_i \qquad (2.11)$$

Thus each 3-D body scan will be characterized by a set of M coefficients, which represent a compact and reliable description.

3. RESULTS

The above method is applied to a subset of the CAESAR database. Three hundred scans of male subjects in the standing posture have been used to extract the eigenpersons. The first 9 eigenpersons are shown in Figure 2. Only the voxels corresponding to positive values are visualized.

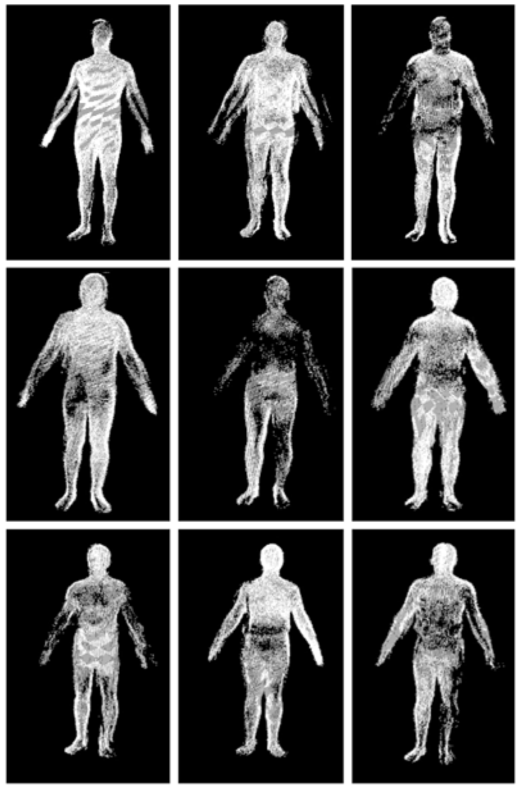

Figure 2. The first 9 eigenpersons. The visualized points correspond to voxels having positive values.

Figure 3 shows the variation of the percentages of the variability as a function of the eigenpersons's number. We notice that 80% of the variability induced by the training set is spanned by 185 eigenpersons.

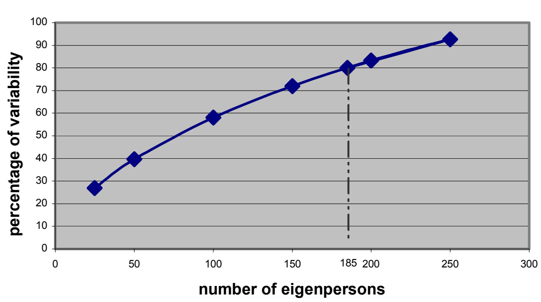

Figure 3 Variation of the percentage of variability with the number of eigenpersons

The original scans of two subjects (Figure 4) included in the training set have been sampled. By using 185 eigenpersons, 100% of points enclosed in the sampled models are reconstructed in both cases.

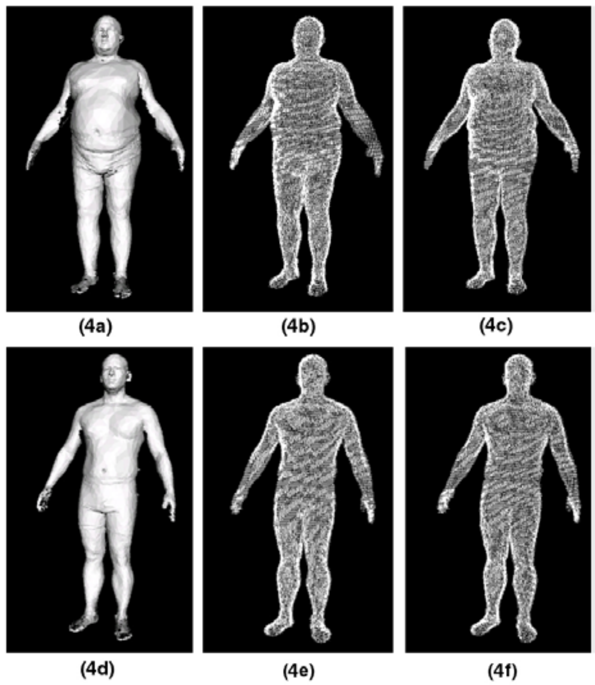

Figure 4. Original scans of subjects included in the training set (4a and 4d), corresponding sampled data (4b and 4e) and reconstructed shapes (4c and 4f).

Figure 5 shows an example of body scan included in the training set. Its reconstruction using 185 eigenpersons generates a model, containing 60.77 % of the total points of the sampled model. A triangulated model(Figure 5d) generated from the reconstructed cloud of point, using innovmetric software [15], shows that the body shape is reconstructed even though around 40% of the points are missing. The distance between the points of the original model and the surface generated from the reconstructed cloud of points are characterized by a distribution having a null mean and a standard deviation equal to 1.2 mm which is less than the sampling interval equal to 5mm.

Using 260 eigenpersons increases the percentage of reconstructed points to 99.73%. The fraction of variability spanned by those eigenpersons is 95% of the total variability.

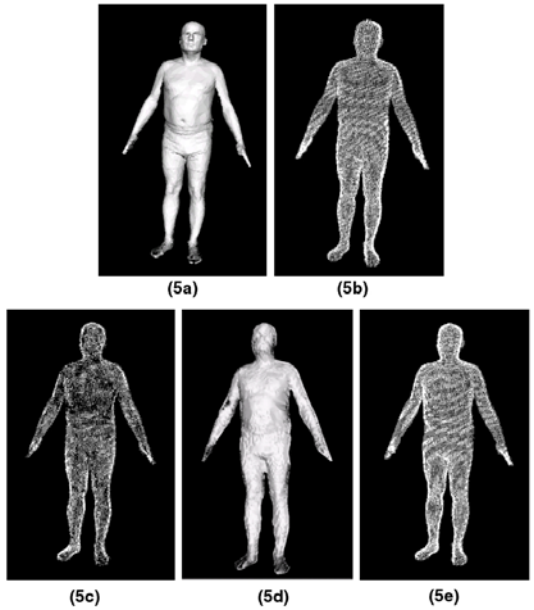

Figure 5. Reconstruction of a subject included in the training set using different numbers of eigenpersons. Original scan (5a), sampled data (5b), reconstruction using 185 eigenpersons (5c), triangulated model generated from the reconstructed cloud of points (5d) and reconstruction with 260 eigenpersons (5e).

Figures 6 and 7 show the reconstructions of two bodies scans not included in the training set used to extract the eigenpersons. In the first case 47% of the points are reconstructed.

In the second case the percentage of reconstructed points is 58%. The distribution of the distance between the original model and the triangulated model generated from the reconstructed cloud of points (figure 6d and 7d) have respectively an average of 1.7mm and 0.5 mm. The standard deviation is respectively of 5mm and 3.99 mm. Again, the quality of the reconstruction is quiet good even though many points are missing.

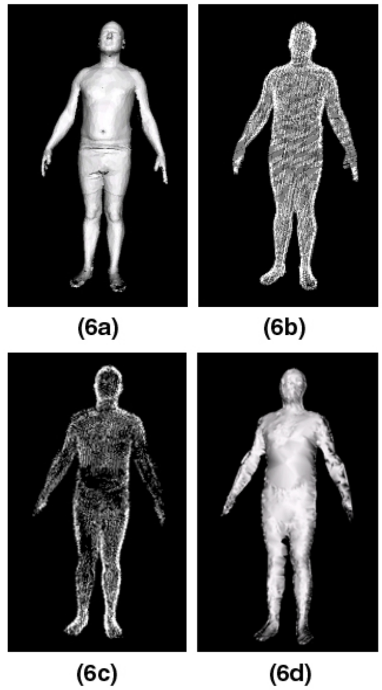

Figure 6: Original scans of a subject non-included in the training set (6a), corresponding sampled data (6b), reconstruction using 185 eigenpersons (6c) and triangulated model generated from the reconstructed cloud of points (6d).

The reconstruction could be improved with an appropriate choice of the training set. It's worth to mention that hands position represents a noisy source of variability within the data set.

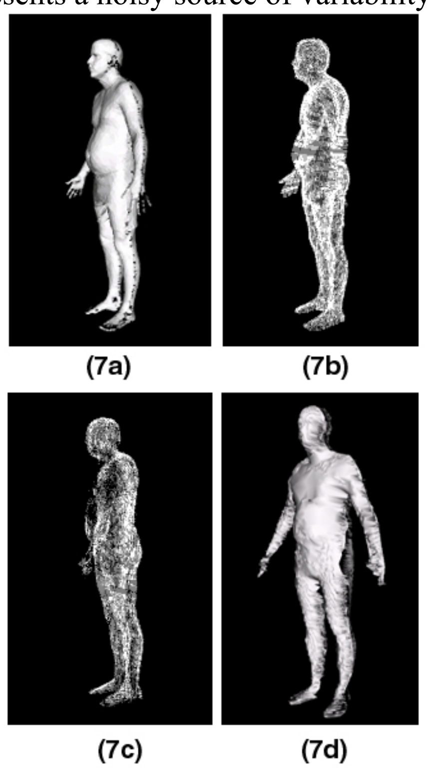

Figure 7: Original scans of a subject non-included in the training set (7a), corresponding sampled data (7b), reconstruction using 185 eigenpersons (7c) and triangulated model generated from the reconstructed cloud of points (7d).

4.Applications

One of the applications of the proposed method is in the understanding of the human shape variability and its distribution for a given population in the design of products such as seats, workstations and clothing. In clothing applications for example, a better understanding of the human shape variability would lead to an improved sizing strategy thereby reducing inventory and unsold items. In computer simulation for the design of automobiles, the method should allow the validation of human models and help in the selection of cases representative of the target population for whom such car models are designed.

5.Conclusion

This paper presents an approach to compactly represent the human body shape and which allows 3D reconstruction for visual evaluation of human models, either real or computer generated. It also provides a new tool for the statistical analysis of 3D anthropometric data such as the ones collected in the CAESAR project. This preliminary study shows that 185 eigenpersons represents 80% of the variability in a set of 300 male subjects.

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