3D Human Head Shape Variation by Using Principal Component Analysis

Yanling Zheng[1], Haixiao Liu[1], Jianwei Niu[1(✉)], Linghua Ran[2], and Taijie Liu[2]

[1] School of Mechanical Engineering, University of Science and Technology Beijing, Beijing, China
niujw@ustb.edu.cn

[2] China National Institute of Standardization, Beijing, China

Abstract. In traditional anthropometry, people adopt the concept of percentile of some critical dimensions, e.g., height. However, percentile has been criticized and its applicability in product design is controversial. Another popular concept in fitting design is sizing, which means to classify human samples into pre-defined categories. Conventionally, sizing scheme usually adopt no more than four dimensions to set up dozens of complex grading charts. However, human head is in 3D form, and limited dimensions can't represent its whole morphologic variation. By the aid of 3D scan technology, there have appeared numerous large-scale 3D human body surveys, as an example, the latest and largest 3D human body survey of Chinese minors conducted by China National Institute of Standardization in the last decade. We used Principal Component Analysis (PCA) as our approach and analyzed 100 3D human head models (all males) and compared their shape variation. The sample data used for our study were taken from 3D human body survey of Chinese minors conducted by China National Institute of Standardization. Our results showed that four principal components described more than 90% of the total variation in the sample. Models of the 3D human head lying on the hyper-ellipsoid constituted by principal component axis have also been re-constructed, using the sample mean and principal components, and they are used to illustrate the variation in human head shape of the sample population, to generate new human head shapes and to reconstruct different human head shapes rapidly. Furthermore, the shape variation carried by each principal component combined distinct factors, e.g., height variation, width variation or depth variation. It is hard to differentiate the specific meaning of each principal component, which made PCA difficult to be used for product designers, tailors and other engineers. Therefore we extended PCA method with a novel regression model to explore the semantic attributes of each principal component. Our method can achieve 3D shape variation quantification efficiently, intuitively and accurately. Experimental results show that PCA on 3D point cloud to realize 3D human head shape variation is an effective method. This method can also find applications in parametric human body modeling, which will greatly reduce the cost of animation and the time of human modeling.

Keywords: Three dimensional (3D) · Human shape variation
Principal Component Analysis (PCA)

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1 Introduction

To quantify the variation of the human head shape is not easy. Traditionally, people adopt the concept of percentile of some critical dimensions, e.g., height. Percentile has been used in product ergonomic design. For instance, in automotive interior design, the 5th percentile of female and the 95th percentile of male are the two extreme interior dimension references. However, percentile has also been criticized and its applicability in product design is controversial. The opponents insist that not all the dimensions of human body will increase or decrease in the same extent simultaneously. In other word, there is no average man on the earth. Percentile only puts great emphasis on some key dimensions, and overlooks other dimensions, even though these dimensions are quite important for fitting design.

Another popular concept in fitting design is sizing, which means to classify human samples into pre-defined categories. Conventionally, sizing scheme usually adopt no more than four dimensions to set up dozens of complex grading charts. Human shape is in 3D form, and limited dimensions can't represent its whole variation. For instance, it's common to find out some persons who share the identical height, chest circumference and waist circumference, but actually their human shapes are not quite the same.

Due to the progress of 3D scan technology, it is easy to get a lot of 3D scanned data. There have appeared numerous large-scale 3D human body surveys in the world, as an example, the latest and largest 3D human body survey of Chinese minors conducted by China National Institute of Standardization in the last decade. In this survey, about 20,000 subjects (9,666 males and 9,699 females) participated. The population database has ages ranging from four to seventeen years old. Our previous work presented the preliminary statistical results of the database mentioned above [1]. Another large scale survey is the Civilian American and European Surface Anthropometry Resource (CAESAR) [2].

It's promising and challenging as well to quantify the human head shape variation directly on 3D human scanned point cloud, among which Principal Components Analysis (PCA) was believed as an attractive and focal method [3, 4]. We used PCA to analyze 100 3D human head models (all males) and compared their main shape variation. The sample data used for our study were taken from the senior high school students group of the 3D human body survey of Chinese minors conducted by China National Institute of Standardization. PCA offers a means of capturing the significant variations in a data sample. Our results showed that four principal components described above 90% of the total variation in the sample. Models of the 3D human head lying on the hyper-ellipsoid constituted by principal component axis have also been re-constructed, using the sample mean and principal components, and they are used to illustrate the variation in human head shape of the sample population, to generate new human head shapes and to reconstruct different human head shapes rapidly.

However, the main shape variation produced by PCA combined distinct factors such as length and width [5]. It is hard to differentiate the specific meaning of each principal component, which made this approach difficult to be used for product designers, tailors and engineers. Therefore we extended PCA method with a novel regression model to explore the space of semantic attributes. For each principal component, a linear mapping between semantic attribute parameters, such as height, and the corresponding shape variations is learned. Our method can achieve 3D shape variation quantification efficiently, intuitively and accurately.

2 Method

2.1 Sample Data

The sample data used for our research is from the latest and largest 3D human body survey of Chinese minors along with their age, weight, height and a key set of body measurements. This survey was conducted by Chinese National Institute of Standardization in the last decade. In this survey, about 20,000 subjects (9,666 males and 9,699 females) participated and 19 anthropometric dimensions were measured. 3D body scanning measuring technique was primarily used, while weight, stature and some other measurements were measured manually. Human Solutions Vitus 3D full body measuring equipment, Human Solutions 3D head measuring equipment, and weighing scales were used. The population database has ages ranging from four to seventeen years old. The children were classified into five age groups: preschool (4–6 ages), junior primary school (7–10 ages), senior primary school (11–12 ages), junior high school (13–15 ages), and senior high school (16–17 ages). The criterion of age stratification is based on ISO15535: 2003 General requirements for establishing anthropometric databases. The population database includes 2,117 pre-school students, 4,263 junior primary school students, 3,930 senior primary school students, 5,527 junior high school students, and 3,527 senior high school students. The subjects were recruited from six geographical areas in China: the northeast-north China, the central and western China, the lower reach of Yangtze River, the middle reach of Yangtze River, the south-east and the south-west China. The sample size in each area was determined based on the distribution of children's population reported by China National Bureau of Statistics. During the measuring process, twenty-one landmarks were stuck on the skin of the subjects to help distinguish these points more easily and conduct template fitting, because some anatomy landmarks can't be recognized by computer software and are not easy to be recognized manually on computer (Table 1).

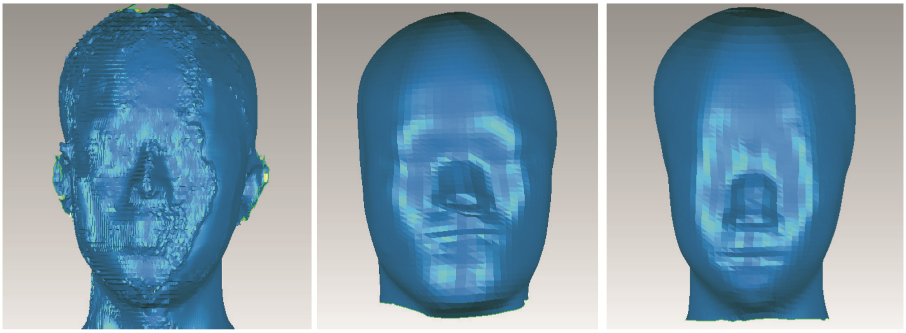
Table 1. Distribution of sample size among age groups

Age	Male	Female	Total
4–6	1043	1074	2117
7–10	2113	2150	4263
11–12	1988	1942	3930
13–15	2795	2732	5527
16–17	1727	1800	3527
Total	9666	9699	1700

2.2 Pre-processing

Because of the light absorption and occlusions, there are holes and noise in the models from the database mentioned above. Besides, in order to apply the PCA to the 3D human head models, all the models must be in correspondence to each other. To be in correspondence means all models under consideration have to contain equal number of points and each point in one model must have a matching point in every other model. Inspired by the work of Anguelov et al. (2005), we used non-rigid template fitting to repair these models and bring all the models into correspondence [6]. This approach is to fit a generic mesh model called the template to every other scan data. The template has to be complete and has well-shaped and well-distributed triangles [7]. The fitting is done by minimizing a weighted combination of data error, smoothness error and landmark error. The data term is to ensure that each vertex of the transformed template is as close as possible to its correspondence vertex of the model. The smoothness term is to make sure that the transformed template is smooth and the landmark term is to avoid getting stuck in a local minimum. The landmarks used for template fitting are the ones placed manually during the measuring process. The ears have complicated geometry and have no effect on this study; therefore, we eliminated ears during pre-processing.

The template fitting requires a human head template as input. To get the template, we calculated the mean values of traditional dimensions, e.g., head length, head width, of the 100 models, and then calculated the Euclidean distance between the mean dimensions and the dimensions of the 100 models. We chose the model whose dimension distance is the closest to the mean dimensions as the template. To get a good trade-off between fitting quality and computational efficiency, we resampled the template to have 5901 points (Fig. 1).



(a) (b) (c)

Fig. 1. Pre-processing of a head model.

2.3 PCA and Reconstruction

PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of linearly uncorrelated variables. The objective of PCA is to find the most significant components and reduce dimensions, since the vectors with low variance can be discarded, and thus not full data needs to be retained to closely approximate the original sample [8]. The template fitting brought all the models in correspondence so that we are able to apply PCA to the point cloud of each model.

In this study, 100 subjects (all males) were chosen as our input. We stacked the points of the models into a $100 \times (5901 \times 3)$ matrix, $\boldsymbol{\Psi}$. The deviation vector, $\boldsymbol{\Phi}$, is calculated by

$$\boldsymbol{\Phi}_{i,j} = \boldsymbol{\Psi}_{i,j} - \frac{1}{100} \sum\nolimits_{i=1}^{100} \boldsymbol{\Psi}_{i,j} \tag{1}$$

PCA of $\boldsymbol{\Phi}$ yields a set of eigenvectors u and score p. Associated with each principal vector is a variance. The vectors are sorted according to the decreasing order of their variances. The deviation vector, $\boldsymbol{\Phi}$, is approximated as

$$\boldsymbol{\Phi} = pu^{+} \tag{2}$$

where u+ means the pseudoinverse of u. An unlimited number of new models who have a realistic appearance but do not look like any models from the example set can be reconstructed using Eq. 2. Experimental results showed that the first 4 principal components represent above 90% of the total variance.

2.4 Semantic Explanation

PCA helps us to characterize the space of human head variation. However, it does not provide an intuitive way to tell the specific meaning of each principal component, such as head length, head width and gender. In this case, this approach is difficult to be used for engineers. Inspired by Blanz and Vetter [9], we extended the existing PCA method with a novel regression model to explore the space of semantic attributes. For each principal component, a linear mapping between semantic attribute parameters, such as head length, and the corresponding shape variations is learned. Here we show how to learn a linear mapping between the attribute parameters and the principal components scores. Suppose we have l attribute parameters, the mapping can be represented as a $(k-1) \times (l+1)$ matrix, $\mathbf{M}$:

$$\mathbf{M} = \left[f_1 \cdots f_l \, 1\right]^{\mathrm{T}} = \mathbf{p} \tag{3}$$

where f_i are the attribute values of a model, and $\mathbf{p}$ are the corresponding PCA scores.

We can assemble the measurements from our database into an $(l+1) \times k$ attribute matrix $\mathbf{F}$ and get $\mathbf{p}$ by applying PCA. Thus we solve for $\mathbf{M}$ as

$$\mathbf{M} = \mathbf{PF}^{+} \tag{4}$$

where $\mathbf{F}^{+}$ is the pseudoinverse of $\mathbf{F}$. After Eq. 4, we can change the value of attribute values, such as a desired weight, which means a new attribute matrix $\mathbf{F}'$. Then we calculate new corresponding PCA scores $\mathbf{P}'$ as

$$\mathbf{P}' = \mathbf{M}\mathbf{F}' \tag{5}$$

We can reconstruct models using Eq. 2 with desired attribute parameters. We can either make them become taller or shorter, and/or fatter or thinner.

3 Results

The results showed that the first 4 principal components explain more than 90% of the shape variation-enough for most practical application. Statistical shape analysis provides intuitive visualization of the shape variation. We applied PCA directly to point cloud, and shape variation lying on each principal component can be visualized by varying the coefficient of the component. We implemented visualization using Matlab 2015 (Mathworks Inc., Natick, MA, U.S.). Figure 2 is a snapshot of the user interface for shape variation visualization. The slider controls the score of a principal component. Four components were provided. These scores determine the head shape. The users were allowed to control each slider to any specific percentile and then the digital head model will be changed accordingly. Thus head shape variation visualization was implemented. Figure 3 shows the shape variations on the first four principal components.

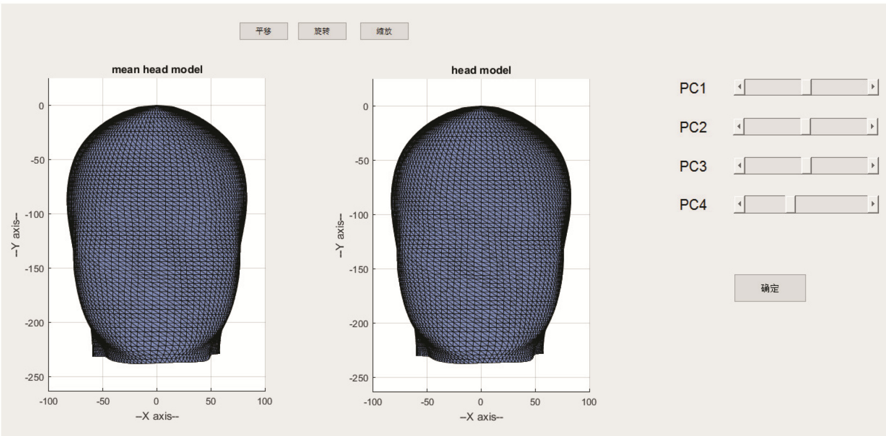


Fig. 2. User interface of the shape variation visualization

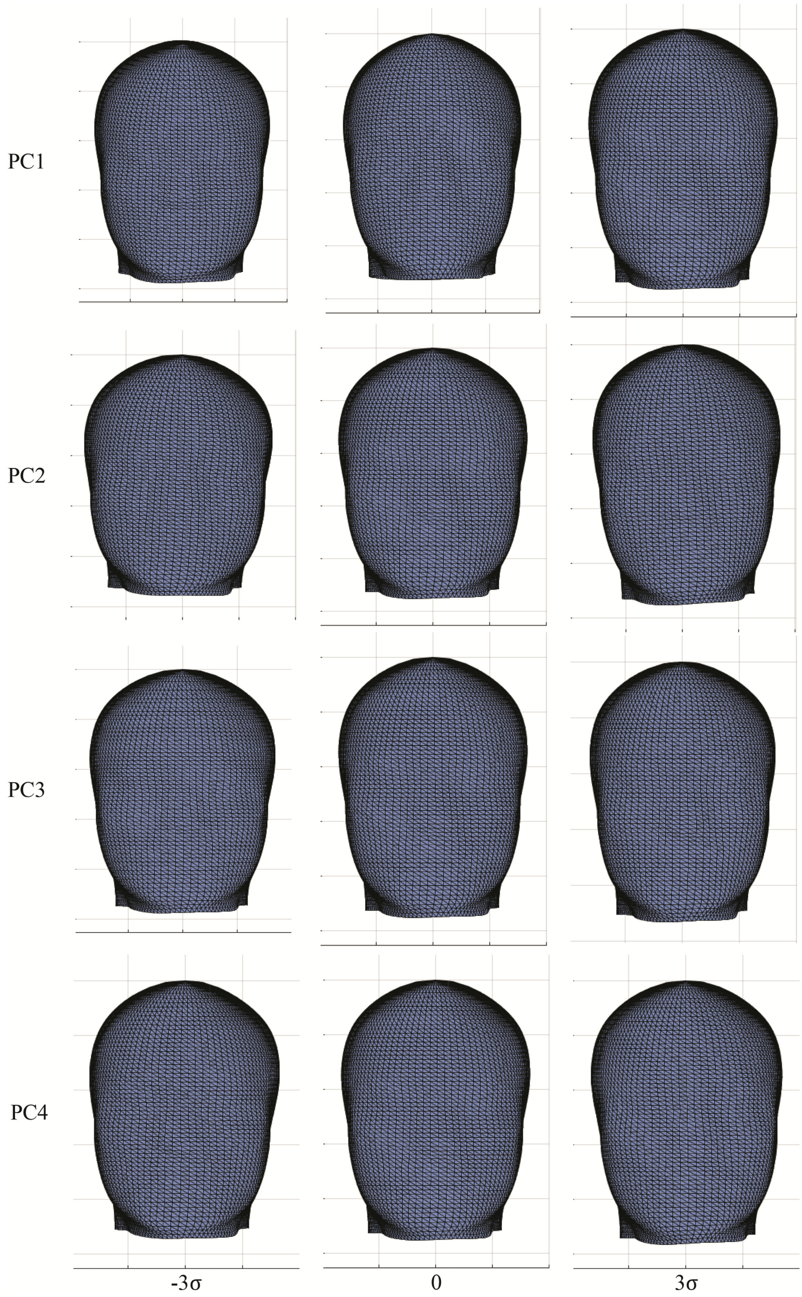


Fig. 3. Shape variations along the first four principal components

The principal components of variation produced by PCA combined distinct factors such as height, weight, girth, fitness, posture and other specific differences in human head shape. It is hard to differentiate the specific meaning of each principal component, which made this approach difficult to be used for engineers. We therefore extended PCA method with a novel regression model to explore the space of semantic attributes. We chose head height, head length, head width and the first four principal components to realize regression. The results of regression are as shown in Fig. 4.

Fig. 4. The results of semantic explanation for head shape variation

4 Discussion

To establish a correspondence among all the models is a very important premise of analysis of 3D scan data. Ben Azouz et al. proposed a volumetric approach [10]. In this approach, every model is embedded in a regular grid and then they oriented and normalized the models carefully. By establishing a correspondence in the grid, a correspondence among the models is established. This method is easy to implement and does not need landmarks. However, the main drawback is that the correspondence is not accurate. Besides, holes have to be filled before correspondence, which consumes resources greatly and proved to be a difficult task because some parts have large holes. We adopted non-rigid template fitting to deal with the problem. The correspondence produced by this approach is accurate and most holes do not have to be filled manually before correspondence establishment.

PCA is believed as an attractive and focal method to quantify the human head shape variation directly on 3D human scanned data. PCA offers a means of capturing the significant variations in a data sample. Point cloud analysis of 3D head scanned data can reveal detailed shape variation among populations and be used for the design of related products. We analyzed 100 3D human head models (all males) and compared their principal modes of variation. Our results showed that four principal components described above 90% of the total variation in the sample. Through PCA analysis on the parameterized models, our results showed significant statistical variations between head shapes of Chinese senior high school students. Human head models lying on the hyper-ellipsoid constituted by principal component axis have also been re-constructed, using the mean sample and principal components, and they are used to illustrate the variation in human head shape. In the future, PCA may be used for three-dimensional sizing as well.

However, the principal components of variation combined distinct factors such as length, width, circumference, posture and other specific differences in human shape. Therefore, we extended PCA method with a novel regression model to explore the space of semantic attributes. We chose three traditional dimensions and the first four principal components to carry out regression. This method is a linear approximation; consequently it may not be completely accurate. Therefore, how to set up the relationship between the principal components and the traditional anthropometric dimensions needs further study.

Our method can achieve 3D shape variation quantification efficiently, intuitively and accurately. Experimental results show that PCA on 3D point cloud to realize 3D human head shape variation is an effective method. This method can also find applications in parametric human body modeling, which will greatly reduce the cost of animation and the time of human modeling.

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