Resolution Influence on 3D Anthropometric Data Clustering for Fitting Design

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Abstract: Sizing based on 3D anthropometric data may lead to significant improvement in fitting comfort of wearing products. However, the required computational load is a common problem in 3D data processing. In a previous study, wavelet analysis was adopted to establish a multi-resolution description of 3D anthropometric data to reduce computational load and modeling complexity. K-means clustering was subsequently performed on the decomposed 3D samples. This study further examines the influence of decomposition level on clustering results. As a case study, 378 face samples, 447 head samples and 432 upper head samples were analyzed. Cluster membership variation on five different resolution levels was examined by using Cluster Membership Accuracy Rate (CMAR), which denotes the clustering consistency on the decomposed levels compared with the clustering results on the original data sets. For the face data sets, the CMAR values on the five decomposition levels are 100, 99.21, 97.88, 93.92 and 93.39%, respectively; for upper heads, the CMAR values are 99.3, 99.1, 98.4, 92.1 and 84.3%, respectively; while for whole heads, the CMAR values are 99.3, 98.2, 95.1, 85.5 and 77.9%, respectively. These results indicate that clustering on the third decomposition level is proper for face and head scans in reducing computational load while maintaining at least 95% clustering accuracy.

Key words: Three dimensional (3D) anthropometry, Population fitting design, Multi-resolution, Clustering, Sizing

Introduction

Considerable attentions have been paid to proper fit of wearing products for a long time^{1–7}). For wearing products which need close fitting, such as helmet, goggle, face mask, spectacles or shoes, they must be designed to well match the human body surfaces of the users. For example, according to a survey of wearing comfort and fit issue of oxygen masks (derived from the Soviet mask system in the 1950s) among 213 Chinese fighter pilots⁸), nearly 80% pilots considered the masks did not fit their faces, and 70% pilots felt masks squeezed their noses and faces, inconvenient to don, doff or adjust. For another example, studies on fitting issue of shoes show that poor fit has been the main source of causing blistering, chafing,

black toes, bunions, pain, and tired feet⁹).

Sizing tariff is one of the most important factors influencing the fit and performance of products^{10, 11}). Some linear measurements were usually used as key dimensions in traditional sizing methods^{12–14}). For example, the current used oxygen mask sizing system for fighter pilots in China is based on the fighter pilots' morphological facial length and bizygomatic breadth or mouth breadth¹⁵). For helmet sizing, head length and head breadth were usually adopted as the key dimensions to group the samples^{16, 17}). However, if only one or two dimensions are taken into account, geometric characteristics and internal structure of human surface are not adequately considered. This may lead to design deficiency on fitting comfort. The demand for new methods arose when traditional sizing systems proved to be inadequate for current cranio-facial design problems.

3D anthropometry surveys, such as the CAESAR pro-

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ject¹⁸⁾, SizeUK¹⁹⁾, SizeUSA (www.tc2.com), SizeChina (www.sizechina.com), etc., can provide tremendous amount of shape information of the human body. Researchers have utilized 3D anthropometric data in the design of helmet²⁰⁾, footwear³⁾, human-harness⁵⁾ and hand tools²¹⁾, etc. However, there exist some difficulties such as high computational load and modeling complexity when using 3D anthropometric data in product design. Multi-resolution can be used to establish a flexible model of 3D data, and then enable data manipulation and analysis progressively in a coarse-to-fine fashion²²⁾. In our previous studies^{23–26)}, wavelet analysis was adopted to establish a multi-resolution description of 3D anthropometric data to reduce computational load and modeling complexity and K-means clustering was subsequently performed on block distance based vectors of decomposed 3D samples to segment a population into groups according to size and shape. This study further examines the influence of decomposition level on clustering results in the case study of upper head, face and whole head samples, and report findings from this case study.

Methodology

Raw Data

The raw data for the case study include head cross sections scans of 510 young male Chinese soldiers (aged from 19 to 23) collected by a military department in 2002. The point number of one head sample varies from minimum 38,826 to maximum 56,200 with an average of 46,400 and standard deviation of 3,117. Noise data on each cross section have been removed manually by visual check under CAD software. The face surfaces were spanned from the whole heads by the front $\pi/2$ wedge angle along a line going through the centroid and pointing to the top of a head. Due to alignment, some unsuitable samples were removed. Therefore, only 378 face samples, 447 whole head samples and 432 upper head samples were derived from the 510 raw data sets and further analyzed.

Multi-resolution representation of 3D surface

Wavelet decomposition was adopted to establish a multi-resolution representation of the 3D data (please refer to Niu *et al.*²⁴⁾ and Niu *et al.*²⁵⁾ for details). The lower resolution part preserves the major information and describes the main shape, while ignores the inappreciable geometric characteristics. By using the lower resolution part instead of the original data sample, shape analysis and comparison can be accomplished to segment the population according to their 3D shape. This model also can help the engineers select appropriate resolution level to customize the wearing product based on specific fitting

requirements.

In the case study, each 3D sample was decomposed under five levels resulting in 3D surfaces with 4,489, 1,225, 361, 121, and 49 control points respectively. From the first to the fifth levels, the number of control points decreases but the major shape of a surface remains with different levels of details.

Block distance-based vector descriptor for sample surfaces

A block distance-based vector descriptor was used for shape clustering. We used the inscribed surface of all the samples as the reference surface. The inscribed surface and all sample surfaces were divided into a predefined number of blocks. The distance between two corresponding blocks on a sample surface i and the inscribed surface, namely $S(i)$, can be constructed with two parts, namely $S_1(i)$ and $S_2(i)$, as

$$S_1(i) = \sum_{j=1}^{n_i} \text{dis}(p_{i,j}), i=1,2,3,\dots,m \quad (1)$$

where $p_{i,j}$ is the j th point, and n_i represents the number of points falling into the i th block, and $\text{dis}(p_{i,j})$ denotes the Euclidean distance between the corresponding points. $S_2(i)$ can be calculated as

$$S_2(i) = \sum_{j=1}^{n_i} \left| \text{dis}(p_{i,j}) - \frac{S_1(i)}{n_i} \right|, i=1,2,3,\dots,m \quad (2)$$

S_2 describes the geometric variation in the corresponding local areas.

From the definitions it can be seen that $S_1(i)$ s mainly reflect size difference of two paired blocks, while $S_2(i)$ s mainly reflect the local shape difference. In such a way, the 3D geometry of a surface can be characterized by a vector $(S_1(1), S_2(1), S_1(2), S_2(2), \dots, S_1(m), S_2(m))$.

K-means clustering

K-means clustering was adopted in this study to classify the population into groups. For k-means clustering, the number of the clusters should be specified beforehand. Currently there are three sizes of oxygen masks in China, i.e., small, medium and large. Wang and Yuan¹⁵⁾ presented a new oxygen mask sizing system where they partitioned the Chinese face samples into four sizes, namely small size, medium-narrow size, medium-wide size and large size. The latest Chinese national standard of 3D craniofacial dimensions for male soldiers partitioned the craniofacial data sets into seven standard head models according to their shapes. In order for the ease of comparison, the number of K for the clustering on face data sets was set as four while that for the clustering on whole head and upper head data sets was set as seven.

Clustering evaluation and cluster membership accuracy rate

K-means clustering based on block distance vectors (If not specially mentioned, block distance were normalized) was applied to the data sets on different decomposition levels and also on original data sets. A criterion for clustering evaluation in this study is size-weighted variance. The size-weighted variances were calculated by pooling the within size variance of block distances. It can be defined as follows,

$$\text{SizeWeightedVar} = \frac{1}{N} \sum_{i=1}^k n_i \times \text{var}(x)_{x \in C_i} \quad (3)$$

where k is the number of clusters, N is the number of the samples, n_i is the number of samples in the k th cluster, C_i denotes the k th cluster, $\text{var}(x)$ denotes the variance of the samples belonging to the cluster C_i . From the definition, a lower value of the size-weighted variance means better clustering.

Besides the size-weighted variances, Cluster Membership Accuracy Rate (CMAR) with respect to various decomposition levels compared to the original surface is also addressed to evaluate the resolution influence on 3D anthropometric data clustering for fitting design. Given the result of clustering on the original data sets as the reference, CMAR of a resolution level i can be defined as follows,

$$\text{CMAR}_i = \frac{N_i}{N} \quad (i = 0, 1, 2, 3, 4, 5) \quad (4)$$

where N_i is the number of samples correctly grouped when compared to the clustering result of the original data sets, and N is the total sample number.

Results and Discussions

Multi-resolution representation and block division

Multi-resolution representation and block division of

face samples, upper head samples and whole head samples were implemented. The result of a face sample is illustrated in Fig. 1, where (a) represents the original face surface, and (b) to (f) correspond to the decomposed face surfaces on the decomposition level of one, two, three, four and five respectively. Quantitative approximation errors were investigated by Niu *et al.*⁽²⁵⁾ with respect to various decomposition levels compared to the original surfaces showing that the decomposed surfaces could preserve the main shape of the original ones before the decomposition level reaches five. For upper heads, the average approximation errors at the 2nd and 3rd decomposition levels are 0.172 mm and 0.457 mm, respectively. In contrast, for faces, the corresponding values are 0.240 mm and 0.702 mm, respectively. For the design of products such as helmets, the approximation error of upper head surfaces at the 3rd decomposition level may be acceptable, while for the design of products such as goggles and respirators, the approximation error of face surfaces at the 2nd decomposition level may be more suitable.

The block division result of a face is shown in Fig. 2.

Fig. 2. Block division of a sample face.

Fig. 1. Multi-resolution model of a face sample (adapted from Niu *et al.*⁽²⁵⁾).

The block division was evenly made along the height and span angle for the studied surfaces, without considering anatomical correspondence. It can be seen that blocks on the forehead are regular patches, while blocks lying in the areas of eyes, nose and mouth are fluctuant and irregular, and their shapes vary evidently between each other. Blocks on the chin area are moderately regular.

Sizing results

Table 1 shows the size-weighted variances of the variables of clustering on different resolutions for faces. Lower values of the size-weighted variances mean that the spread degree of the block distances is smaller. As shown in Table 1, the ratios of size-weighted variances are all equal to and close to 1 although some limited variations can be observed. This may imply that the clustering results under different decomposition levels are

Table 1. Size-weighted variances for faces on different decomposition levels ($N=378$, 20 blocks each face)

variable	Size-weighted variances				Ratio of size-weighted variances		
	Original	Level 1	Level 3	Level 5	Level 1 vs. original	Level 3 vs. original	Level 5 vs. original
$S_1(1)$	0.53	0.53	0.52	0.52	1	0.98	0.98
$S_1(2)$	0.46	0.46	0.46	0.51	1	1	1.11
$S_1(3)$	0.47	0.47	0.47	0.53	1	1	1.13
$S_1(4)$	0.43	0.43	0.43	0.47	1	1	1.09
$S_1(5)$	0.48	0.48	0.47	0.47	1	0.98	0.98
$S_1(6)$	0.34	0.34	0.34	0.36	1	1	1.06
$S_1(7)$	0.35	0.35	0.34	0.32	1	0.97	0.91
$S_1(8)$	0.33	0.33	0.33	0.32	1	1	0.97
$S_1(9)$	0.36	0.36	0.34	0.31	1	0.94	0.86
$S_1(10)$	0.33	0.33	0.33	0.36	1	1	1.09
$S_1(11)$	0.27	0.27	0.27	0.27	1	1	1
$S_1(12)$	0.23	0.23	0.23	0.23	1	1	1
$S_1(13)$	0.27	0.27	0.26	0.25	1	0.96	0.93
$S_1(14)$	0.24	0.24	0.24	0.23	1	1	0.96
$S_1(15)$	0.28	0.28	0.28	0.27	1	1	0.96
$S_1(16)$	0.35	0.35	0.35	0.35	1	1	1
$S_1(17)$	0.27	0.27	0.27	0.29	1	1	1.07
$S_1(18)$	0.25	0.25	0.25	0.27	1	1	1.08
$S_1(19)$	0.27	0.27	0.28	0.27	1	1.04	1
$S_1(20)$	0.36	0.36	0.37	0.36	1	1.03	1
$S_2(1)$	0.83	0.83	0.85	0.64	1	1.02	0.77
$S_2(2)$	0.68	0.68	0.64	0.57	1	0.94	0.84
$S_2(3)$	0.7	0.7	0.65	0.61	1	0.93	0.87
$S_2(4)$	0.64	0.64	0.62	0.59	1	0.97	0.92
$S_2(5)$	0.76	0.76	0.72	0.57	1	0.95	0.75
$S_2(6)$	0.7	0.7	0.64	0.68	1	0.91	0.97
$S_2(7)$	0.77	0.77	0.78	0.5	1	1.01	0.65
$S_2(8)$	0.64	0.64	0.58	0.61	1	0.91	0.95
$S_2(9)$	0.89	0.89	0.87	0.6	1	0.98	0.67
$S_2(10)$	0.85	0.85	0.8	0.8	1	0.94	0.94
$S_2(11)$	0.9	0.9	0.91	0.99	1	1.01	1.1
$S_2(12)$	0.65	0.65	0.66	0.68	1	1.02	1.05
$S_2(13)$	0.84	0.84	0.79	0.95	1	0.94	1.13
$S_2(14)$	0.74	0.74	0.73	0.72	1	0.99	0.97
$S_2(15)$	0.88	0.88	0.9	0.84	1	1.02	0.95
$S_2(16)$	0.86	0.86	0.84	0.84	1	0.98	0.98
$S_2(17)$	0.72	0.72	0.76	0.82	1	1.06	1.14
$S_2(18)$	0.72	0.72	0.72	0.75	1	1	1.04
$S_2(19)$	0.79	0.79	0.84	0.86	1	1.06	1.09
$S_2(20)$	0.86	0.86	0.87	0.88	1	1.01	1.02

$S_1(i)$ - the first part of block-based distance between two blocks; $S_2(i)$ - the second part of block-based distance between two blocks; i - No. of a block.

quite consistent. To further confirm it, CMAR values should be examined.

Given the result of clustering on the original data sets as the reference, cluster membership variation on different resolution level of each sample was investigated by using the CMAR, as summarized in Table 2. For the face data sets, the numbers of improper clustering samples on the first, second, third, fourth and fifth decomposition levels are 0, 3, 8, 23 and 25 respectively (sample size is 378). CMAR values on the five decomposition levels are 100, 99.21, 97.88, 93.92 and 93.39% respectively. These values are very high. For the upper head data sets, the numbers of improper clustering samples on the first, second, third, fourth and fifth decomposition levels are 3, 4, 7, 34 and 68 respectively (sample size is 432). CMAR values on the five decomposition levels are 99.3, 99.1, 98.4, 92.1 and 84.3% respectively. That is, until the fifth decomposition level CMAR drops to be lower than 90%. As for whole head data sets, the numbers of improper clustering samples on the first, second, third, fourth and fifth decomposition levels are 3, 8, 22, 65 and 99 respectively (sample size is 447), corresponding to CMAR val-

ues of 99.3, 98.2, 95.1, 85.5 and 77.9% respectively, showing a more quick CMAR drop with decomposition level, but CMAR values until decomposition level 3 are still very high (>95%), although the control point number has dropped from 4,489 to 361. Therefore, such high CMAR values indicate that wavelet decomposition level has inconspicuous influence on the shape clustering before the decomposition level reaches four. This strengthens the conclusion made by Niu *et al.*²⁴⁾ and Niu *et al.*²⁵⁾ that data set at a lower resolution can preserve the major information and describes the main shape of the original 3D form. To sum up the previous analysis, as for 3D craniofacial data sets, k-means clustering on the decomposed data set other than on the original one can likewise result in appropriate sizing for the purpose of population fitting design.

The above discussion is based on a practical viewpoint and related standards. The most common accommodation rates adopted in product design are 90% and 95%. We may say 92.1% differs from 84.3% since there is greater difference between them and 84.3% is lower than 90%. On the contrast, it's not meaningful to distinguish

Table 2. Cluster membership statistics

Cluster ID	Cluster size					
	Original	Level 1	Level 2	Level 3	Level 4	Level 5
Face data sets, $N=378$, 20 blocks each sample						
1	52	52	52	52	51	59
2	60	60	59	57	54	55
3	136	136	135	137	143	134
4	130	130	132	132	130	130
Improper clustered samples	...	0	3	8	23	25
CMAR (%)	...	100	99.21	97.88	93.92	93.39
Upper head data sets, $N=432$, 20 blocks each sample						
1	92	92	92	91	94	91
2	55	55	55	56	55	52
3	82	81	81	83	80	91
4	35	35	34	34	33	31
5	68	70	71	69	70	76
6	35	34	34	35	36	35
7	65	65	65	64	64	56
Improper clustered samples	...	3	4	7	34	68
CMAR (%)	...	99.3	99.1	98.4	92.1	84.3
Whole head data sets, $N=447$, 20 blocks each sample						
1	61	60	61	60	57	56
2	57	57	58	55	64	65
3	53	53	54	55	55	39
4	91	91	88	87	79	94
5	57	57	59	63	70	75
6	34	34	34	33	32	35
7	94	95	93	94	90	83
Improper clustered samples	...	3	8	22	65	99
CMAR (%)	...	99.3	98.2	95.1	85.5	77.9

CMAR - Cluster Membership Accuracy Rate.

93.9% and 93.4%, since the difference is so small and both are higher than 90%. As to related standards, taking respirator as an example, annual fit testing is required under OSHA's respirator standard 29 CFR 1910.134²⁷⁾ and recommended by the ANSI guidelines for respiratory protection (ANSI Z88.2-1992)²⁸⁾. Respirators designed to fit these panels were expected to accommodate at least 95% of the wearers. Considering the contact interfaces of such kind of products would have a certain level of adjustability and flexibility, a little lower than 95% can

be considered for judgment of acceptable CMAR since it is based on rigid surface analysis.

Average sample of a cluster can be used as the representative sample of the cluster. It can be generated by averaging coordinates of corresponding points of all the samples belonging to the same cluster. Taking face data sets as an example, different views of the merged average face samples of the clusters ($N=378$) on different decomposition levels are shown in Fig. 3. The figure can be helpful to obtain an intuitive understanding of the clus-

Fig. 3. Different views of the merged average faces of clusters ($N=378$).

tering results and the shape dissimilarity among clusters.

Conclusions

In this paper, the influence of decomposition level on clustering results of 3D face data sets, upper head data sets and whole head data sets were studied. Cluster membership accuracy rates (CMARs) on different resolution levels, namely from the first to the fifth decomposition levels, were investigated. Results indicate that clustering on the third decomposition level is proper for face and head scans in reducing computational load while maintaining at least 95% clustering accuracy. High CMAR values imply that wavelet decomposition level does not have remarkable influence on shape clustering before the decomposition level reaches five. Considering the difference of the interface of different products with human body surface, engineers could be encouraged to adopt the CMAR value as a valuable reference to select a proper decomposition level for the design of a specific product based on the corresponding fitting requirement.

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