LETTER

Sexual Dimorphism Analysis and Gender Classification in 3D Human Face

Yuan HU[†a)], **Li LU**[†], ***Student Members***, **Jingqi YAN**[†], **Zhi LIU**[††], ***and*** **Pengfei SHI**[†], ***Nonmembers***

SUMMARY In this paper, we present the sexual dimorphism analysis in 3D human face and perform gender classification based on the result of sexual dimorphism analysis. Four types of features are extracted from a 3D human-face image. By using statistical methods, the existence of sexual dimorphism is demonstrated in 3D human face based on these features. The contributions of each feature to sexual dimorphism are quantified according to a novel criterion. The best gender classification rate is 94% by using SVMs and Matcher Weighting fusion method.This research adds to the knowledge of 3D faces in sexual dimorphism and affords a foundation that could be used to distinguish between male and female in 3D faces.

key words: *gender classification, sexual dimorphism, SVMs, 3D face classification*

1. Introduction

The human face presents a clear sexual dimorphism that makes face gender recognition an extremely efficient and fast cognitive process.Gender classification has attracted a lot of attention in the computer vision [1]–[3], as well as in psychological literature [4], [5]. In computer vision research, gender classification plays prominent roles in human identification, face recognition, intelligent human-computer interfaces, computer vision approaches for monitoring people, passive demographic data collection, etc. Although psychological research has shown that gender has close relationships both with 2D information and 3D shape [6], most of the works are based on 2D face images, only a few studies have investigated 3D shape gender classification [7], [8]. This is due to the high price of 3D sensor and complex computation of 3D information. Especially, the 3D computation result is not as good as the result based on 2D information. In Xiaoguang Lu's research [7], he combined the registered range and intensity images for gender identifications using a support vector machine. Jing Wu [8] presented weighted principal geodesic analysis (PGA) and supervised PGA to parameterize the facial needle-maps and compared their performances with PGA for gender classification.

In this paper, we concentrate on replying to three questions: 1) Does dimorphism exist in 3D human face? 2) Which features on 3D human face have more contribution? 3) Why classify the gender based on 3D shape of human face? To answer these questions, four categories of features are extracted from 3D human face shape captured by 3D scanner in our analysis. We estimate the existence of dimorphism based on these features and analyze which features are more significant in the exhibition of sexual dimorphism. Our goal here is to quantify sexual dimorphism to help to understand the degree and extent of dimorphism in 3D human face. In addition, the gender of 3D human face is automatically recognized based on the features which are the most prominent in the analyses.

Specific contributions of this paper are to: 1) add to the knowledge of 3D faces in sexual dimorphism; 2) analyze the distributions of features and provide quantitative results of sexual dimorphism on 3D human face shape; 3) establish a foundation that could be used to distinguish between male and female 3D faces.

The outline of the paper is organized as follows. Section 2 describes four types of statistics extracted from 3D human face for classification. The analysis of existence of sexual dimorphism of 3D faces and the contribution of features are presented in Sect. 3. Section 4 provides the gender classification rates in our experiments and the results of fusion. Finally, conclusions are provided in Sect. 5.

2. Feature Extraction

The University of Notre Dame Biometrics Database [9] used in this research has a large number of 2D and 3D face images which are collected using the Minolta Vivid 900 3D scanner and is rich in variety, with different categories of gender, ethnicity and identity being well represented. The 2D and 3D images are pixel to pixel. Only the frontal dataset is used in this research, which contains 734 frontal scans of 213 individuals, composed of 432 scans of 125 males and 302 scans of 88 females. For easy manipulation, a commercial software, called Luxand FaceSDK [10] is currently used to extract feature points from 2D image. Luxand FaceSDK provides the coordinates of 40 facial feature points for further processing. After using this software, we select 23 feature points to analysis and check the positions of feature points. These points are grouped into five groups: face contour, eyebrows, eyes, nose and mouth. Figure 1 shows the location of the 23 feature points collected from a sample face.

Based on the positions of 2D feature points, a set of the corresponding coordinates of 3D feature points $S = \{(x, y, z)\}$ are obtained. After translation and rotation, the points are normalized to $S' = \{(x', y', z')\}$ so that the nose tip are located at origin and the line passes the outside cor-

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[†]The authors are with Institute of Image Processing and Pattern Recognition, Shanghai Jiao Tong University, 200240 China.
[††]The author is with Shandong University, China.
a) E-mail: huyuan@sjtu.edu.cn
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Fig. 1 Features extracted from a sample face.

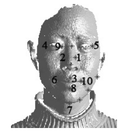


Fig. 2 The first ten significant point features.

ner of left eye and right eye is parallel to x-axis.

Thus according to the coordinates we calculate four types of statistics: 1) 66 3D point coordinates; 2) 253 Euclidean distances between any two points; 3) 31878 Ratios of any two distances; 4) 31878 Angels between any two straight lines which are through any two points respectively.

3. Analysis of Dimorphism

In this section, the sexual dimorphism is analyzed in the 3D human face. Our research is organized around answering some fundamental questions about sexual dimorphism in 3D human face, the questions are:

Question 1: Does sexual dimorphism exist in the shape of 3D human face? If it does, can this be quantified?

Question 2: Which shape features contribute the most to dimorphism of the faces?

For Question 1, typical statistical approaches are used to analysis the differential of the male and female. A new method of feature selection is found to give a score of contribution for each feature to Question 2.

3.1 3D Face Dimorphism

In this section, two statistical analyses, T-test and F-test, are used to determine if dimorphism exists between the 3D shape of male and female faces. The two-sample T-test is used to determine if two population means are equal. It evaluates whether the features of male and female are statistically different from each other. An F-test is used to test if the standard deviations of two samples are equal. With T-test and$F$-test, the existence of dimorphism in 3D human face can be demonstrated.

T-test:

$$t = \frac{x_1 - x_2}{\sqrt{\frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{(n_1+n_2-2)}\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}} \tag{1}$$

F-test:

$$f = \frac{s_1^2}{s_2^2} \tag{2}$$

where, x_1 and x_2 indicate the means of the males and females, n_1 and n_2 refer to the number of males and females respectively; s_1 and s_2 are the standard deviation of males and females.

At 0.05% false accept rate, 47 features of points coordinate can be discriminated, 186 features of distances are differentiated, 11094 features of ratio can be distinguished and 14576 features of angles are different. The results of the experiment show that dimorphism exists in 3D human face undoubtedly.

3.2 Analysis of Contribution

In this section, the contributions of the features are quantified for sexual dimorphism through our criterion. For two samples $(X_1, \ldots, X_n)$, $(Y_1, \ldots, Y_n)$the criterion is formulated as:

$$G = \frac{\left|\bar{X} - \bar{Y}\right|}{\sigma_X + \sigma_Y} \cdot F \tag{3}$$

where,

$$F = \begin{cases} \frac{\sigma_X}{\sigma_Y}, if\, \sigma_Y \geq \sigma_X, \\ \frac{\sigma_Y}{\sigma_X}, if\, \sigma_Y < \sigma_X \end{cases}$$

$\bar{X}$, $\bar{Y}$ indicate the means of the males and females, σ_X, σ_Y refer to the standard deviation of the males and females. G is the weight of the contribution to sexual dimorphism.$\left|\bar{X} - \bar{Y}\right|$is the absolute value of differences between two samples' means, which is directly rational to G, $\sigma_X + \sigma_Y$is inversely rational to G, F is the ratio of the standard deviations of two samples, which is also directly rational to G. $F \in [0, 1]$, if F is close to 1 which denotes the differences of the standard deviation is small, else if F is close to 0 which denotes the differences of the standard deviation is large.

The features of the male and female, which means difference is significant and standard deviations are quite small and almost equal to each other, will get a higher G-value, that indicate more contribution to sexual dimorphism.

In our experiments, we calculate the G-value of all features and analyze the contribution for each category. The first ten significant point features which have higher G-value are shown in Fig. 2. The most significant point feature is around the nose, 90% most significant features are distributed around nose, eyes and mouth. The experiment results in Sect. 4.1 show that the classification rate is 84 % based on the first ten significant point features. The first ten significant distance features which have higher G-value are shown in Fig. 3. These features are distributed on nose, eyes and mouth. The first ten significant ratio features which have higher G-value are shown in Fig. 4. The first ten significant angle features which have higher G-value are shown in Fig. 5. Table 1 shows the average of the first ten significant features of each type for male and female. G means the G-values of the features. M and F mean the average

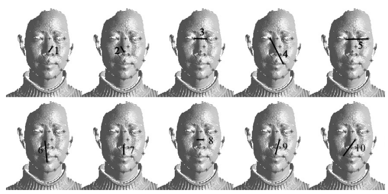


Fig. 3 The first ten significant distance features.

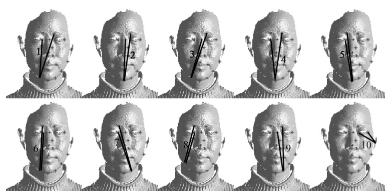


Fig. 4 The first ten significant ratio features.

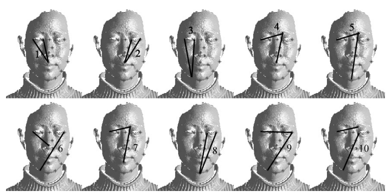


Fig. 5 The first ten significant angle features.

Table 1 The first ten significant features of each type for male and female.

	Points			Distance			Ratio			Angle		
k	G	M	F	G	M	F	G	M	F	G	M	F
1	0.284	−47.07	−44.77	0.253	18.08	16.71	25.221	0.85	0.83	11.188	20.31	19.56
2	0.216	34.39	31.45	0.215	19.44	17.95	24.304	0.84	0.83	10.111	20.33	19.71
3	0.175	−44.50	−37.99	0.204	40.41	36.92	23.646	0.84	0.83	9.525	13.92	13.48
4	0.160	−18.00	−17.02	0.186	62.13	58.06	23.161	0.82	0.81	9.515	64.92	67.04
5	0.132	32.66	30.26	0.181	69.86	65.23	22.316	0.87	0.86	9.483	112.21	110.36
6	0.117	−36.11	−30.32	0.176	43.30	39.67	21.818	0.88	0.86	9.407	72.74	70.21
7	0.105	18.06	17.14	0.171	28.65	26.34	19.582	0.86	0.85	9.313	65.81	67.56
8	0.099	32.49	30.29	0.168	19.52	18.42	18.720	0.90	0.89	9.254	14.85	14.50
9	0.093	−34.86	−28.76	0.166	49.02	44.90	18.207	0.81	0.80	9.097	107.08	105.94
10	0.092	47.34	45.24	0.155	69.04	64.72	16.653	0.73	0.72	8.762	103.86	101.25

point coordinates (distances, ratios, angles) of male and female, respectively. These values are sorted depending on the G-values. G-value is not only related to the difference of means, but also affected by the size and proportion of variances.

4. Gender Classification

4.1 Face Classification Based on Features

The goal in this experiment is to determine how well we could expect to perform the task of gender classification, by using these four categories of features. The features are arranged in a queue depending on the significance calculated by G-value criterion in Sect. 4.2. Support Vector Machines [11], which provide high gender classification accuracy, is used to determine each observation into male and female group by increasing the number of features. The database used in our experiments contains 734 3D frontal scans, including 432 males and 302 females. 50 males and 50 females are extracted randomly for test, others for train.

Table 2 Classification rates of point features.

Number of features	10	20	30	40	50	60	66
Classification rate	84%	82%	91%	94%	93%	93%	92%

Table 3 Classification rates of distance features.

Number of features	10	25	50	75	100	150	200	253
Classification rate	92%	93%	93%	92%	92%	94%	93%	93%

Table 4 Classification rates of ratio features.

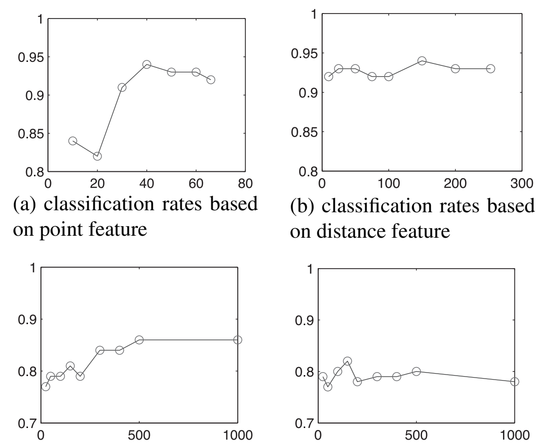
Number of features	25	50	100	150	200	300	400	500	1000
Classification rate	77%	79%	79%	81%	79%	84%	84%	86%	86%

Table 5 Classification rates of angle features.

Number of features	25	50	100	150	200	300	400	500	1000
Classification rate	79%	77%	80%	82%	78%	79%	79%	80%	78%

Table 6 The comparison of the results between PCA and G-value criterion.

	Point	Distance	Ratio	Angle
PCA + SVMs	80%	76%	63%	67%
G-value Criterion + SVMs	94%	94%	86%	82%



(a) classification rates based on point feature

(b) classification rates based on distance feature

(c) classification rates based on ratio feature

(d) classification rates based on angle feature

Fig. 6 Classification rates of gender.

Table 2–5 show the classification rates from four categories of features. The best classification rate is 94% when using the most 40 significant point features; for distance feature, the best classification rate is 94%. While, the best classification is 86% for ratio features and 82% for angle feature. Figure 6 shows the graphical representation of Table 2–5, with classification rate in vertical axis and steps in horizontal axis.

For comparing, we also using PCA + SVMs to classify depending on 23 feature points extracted by Luxand FaceSDK. Table 6 shows the comparison of the results between PCA + SVMs and G-value criterion + SVMs.It shows that G-value criterion + SVMs gets a higher classification

Table 7 The classification rates with four fusion methods.

Fusion method	SS	MIS	MAS	MW
Male classification rate	94%	80%	98%	98%
Female classification rate	86%	100%	64%	90%
Total classification rate	90%	90%	81%	94%

rates than PCA + SVMs in the condition of the 23 feature points extracted by Luxand FaceSDK.

4.2 The Fusion Method

The gender classification is formulated as a two-class classification problem. In Sect. 4.1, the posterior probabilities of features are extracted through SVMs, instead of matching scores. We experimented with four different fusion methods, namely, simple-sum, min-score, max-score, and matcher weighting [12]. The quantity n_i^m represents the normalized probabilities for features $m(m = 1, 2, \ldots, M)$ applied to user i ($i = 1, 2, \ldots, I$, where I is the number of individuals in the database). The fused probability for user i is denoted as f_i .

- Simple-sum (SS): $f_i = \sum_{m=1}^{M} n_i^m$
- Min-Score (MIS): $f_i = min(n_i^1, n_i^2, \ldots, n_i^M)$
- Max-Score (MAS): $f_i = max(n_i^1, n_i^2, \ldots, n_i^M)$
- Matcher Weighting (MW): $f_i = \sum_{m=1}^{M} w_i^m n_i^m$,

where, $w_i^m = \frac{1}{r^m \cdot \sum_{m=1}^{M} \frac{1}{r^m}}$

The fusion classification rates using different fusion methods are shown in Table 7. The best total classification rate is obtained 94% using Matcher Weighting (MW) method.

5. Conclusion

Differing from previous 2D face gender research, we use 3D human face and deeply analyze the sexual dimorphism in the 3D faces. Based on the four types of features, experiment results demonstrate that sexual dimorphism is widespread on 3D human face by using statistical methods. According to G-value criterion, features are arranged based on the score of significance, which represents the contribution to sexual dimorphism. SVMs are used to classify each observation into either the male or female group. The best gender classification rate is 94% using Matcher Weighting fusion method. The result of this research can be used to help automated gender classification system based on 3D faces.

Acknowledgments

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