Geometric-based Feature Analysis of Differences between Western and East-Asian Expressive Faces Based on Principal Component Scores

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Abstract - Darwin was the first one to assert that facial expressions are innate and universal, which are recognized across all cultures. However, recently some cross-cultural studies have questioned this assumed universality. Therefore, this paper presents an analysis of the differences between Western and East-Asian faces of the six basic expressions (anger, disgust, happiness, sadness and surprise). The analysis is conducted by handling 163 feature points from different facial parts, based on an Eigenspace obtained by applying PCA. As a consequence, we can evaluate differences and similarities qualitatively and quantitatively by using its Principal Component Scores. The analysis reveals that exist some differences between Westerns and East-Asians, especially for expressions of disgust and fear meanwhile there is a high level of similarities for the rest of the basic expressions.

Keywords: facial expression analysis, cultural specificity of emotions and PCA

1. INTRODUCTION

More than one hundred years ago, Charles Darwin in his work called "The Expression of the Emotions in Man and Animals" postulated that facial expressions are innate and invariant for human beings and some mammals [1]. Since then, many psychologists have agreed on the universal hypothesis which proposes that all humans show six basic internal emotional states: anger, disgust, happiness, sadness and surprise. Therefore, these basic emotions are straight linked with its respective facial expressions [2].

Based on the universal hypothesis, facial expressions have long been considered as the universal language to represent internal emotional states, recognized across all different races and cultures. However, recently some researchers have questioned and in some degree refuted this assumed universality. Dailey et al. [3] examined the effect of culture-specific facial expression understanding by analyzing the recognition capability of U.S. and Japanese participants. In Dailey's experiment, both groups of people were asked to categorize facial expression from American and Japanese databases, they conclude that each group was better than the other at classifying facial expressions posed by members of the same culture. In a more recent study, Jack et al. [4] claim to refute the universal hypothesis by analyzing the perception of emotional facial expressions using reverse correlations of viewers' classifications of randomly generated muscle movements (developed using a computer graphics platform). Jack's cross-cultural comparisons show that whereas Westerns represent each of the six basic emotions with a distinct set of facial movements common to the group, Easterners do not.

In summary, cross-cultural studies have found differences on showing and recognizing facial expressions between cultures, concluding that facial expressions could be defined as culture-specific instead of universal. However, this studies did not analyze the differences which are known to appear between cultures, therefore an analysis of mentioned differences may serve on the way to facial expressions understanding.

In this paper, we present an analysis of the differences and similarities between Western and East-Asian expressive faces from different facial regions. The analysis is conducted by employing geometric features which represent the shape of the whole face and individual facial parts by extracting 163 feature points. In order to obtain the most important characteristics from the face, we utilized Principal Component Analysis (PCA) which is a well-known feature extraction algorithm, used even for facial expression recognition [5]. A relevant issue form this analysis is that based on the Eigenspace obtained by applying PCA to the complete dataset, we can evaluate differences and similarities from the projections of the 6 basic expressions qualitatively and quantitatively based on its principal component scores.

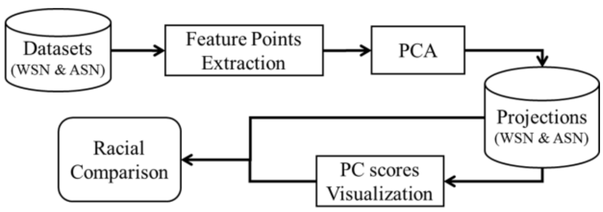

Fig. 1. Proposed method for the analysis.

2. METHOD

In order to correctly analyze the differences between Western (WSN) and East-Asian (ASN) expressive faces, we proposed a method based on PCA application for obtaining shape projections as shown in Figure 1.

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The purpose of this method is to generate an Eigenspace employing information of both racial groups (WSN and ASN) which is used for obtaining individual projections of each expressive face so as to be compared with those from the opposite racial group. It is worth noting that this comparison is performed in visual as well as in analytic way based on principal component scores.

2.1 Feature Points Extraction

As mentioned before, the whole shape is defined by 163 feature points which were obtained from each facial image by using a GUI-based system based on manual operation to pick up each feature point from the face. Of course, we may use the automatic extraction methods of feature points, if they provides the sufficient accuracy.

An example of a whole facial shape obtained by this process is shown in Figure 2(a). In the same Figure, individual facial parts are also presented, where 28 and 26 feature points are used to define the shapes of eyebrows and eyes respectively, shown in Figure 2(b), 42 for lips' shape 2(c), 29 for nose's shape 2(d) and 38 for face outline 2(e).

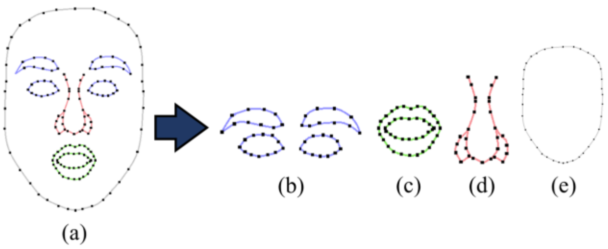

Fig. 2. Shape of expressive face based on 163 feature points.

2.2 Principal Component Analysis

The purpose of PCA is to build a space which better describes the complete set of input data set. This space is called Eigenspace and its basis vectors are called principal components (PC). These components will be uncorrelated and will maximize the variance of the original data set.

In general, the procedure for obtaining the Eigenspace begins by handling the shapes of the face as column vectors of N-dimensions, where N depends on the number of feature points for each facial part, e.g. N=42 for lips' shape. Subsequently, PCA employs the covariance matrix of the complete set of shapes under analysis for obtaining its eigenvectors which finally will define the Eigenspace as principal components. For this process the whole dataset was used, including shapes of expressive faces from both races.

Finally, projections of each individual face were calculated which were divided by race (WSN & ASN) and by expression. It is worth noting that the dimension of projected vector can be equal to N just if all of the PC of Eigenspace are taken in this process.

2.3 Principal Component Scores Visualization

The PC scores contained in each projection is the most valuable information that can be get from PCA process. Therefore, for a better understanding of these scores, we used the Drawface tool developed by Kaneko et al. [6] which shows the behavior of PC scores by drawing a caricaturized face generated by a shape vector projected on a previously defined Eigenspace. The caricature is drawn based on the mean shape of the faces calculated from the complete dataset, which in turn is composed by the mean shape of each facial part.

It is important to mention that this tool allows to individually manipulate the score of each PC. Hence, we can easily observe the behavior of the information in a visual way. Figure 3 show an example of the process for obtaining caricaturized faces from projections made on the Eigenspace, going through the steps of feature points extraction (Facefit), projection calculation (PCA) and PC visualization (Drawface).

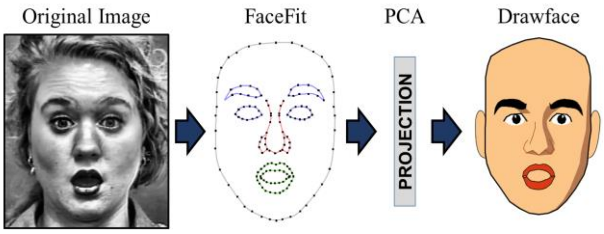

Fig. 3. Process for applying Drawface tool.

3. DATASETS

For this paper two different datasets are needed, one composed for Western people (WSN) and other for East-Asian people (ASN). In order to conform these datasets, we used four different standard databases which are some of the most used in cross-cultural studies.

WSN dataset contains 240 facial images (40 images per expression) selected from the Extended Cohn-Kanade database (CK+) [7] which comprises 327 facial image sequences from 123 subjects performing the 6 basic emotions. For this paper, the subset selected from CK+ only includes images of Euro-American subjects.

ASN dataset is comprised by 240 frames selected from three standard datasets, JAFFE database [8] which includes 213 images from 10 Japanese female models; JACFEE database [9] which contains 56 images from different individuals including 28 Japanese and 28 Caucasian subjects; and TFEI database [10] which consists of 336 images from 40 Taiwanese models (20 males).

Figure 4 shows an example of the six basic expressions (from left to right: anger, disgust, fear, happiness, sadness and surprise) included in WSN and ASN datasets. Not shown are the images selected from JACFFE (Japaense people only) which cannot be reprinted due to copyright restrictions.

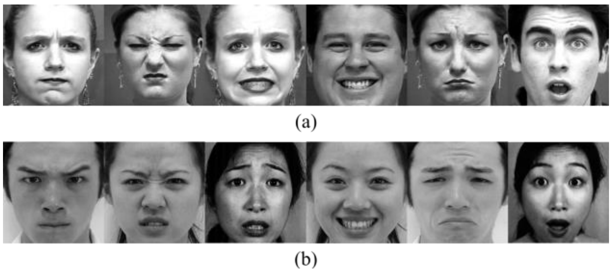

Fig. 4. Example of datasets. (a) WSN and (b) ASN datasets.

4. ANALYSIS EVALUATION

According to the PCA basics, each projection made on the Eigenspace may contain the most relevant information. In other words, the information contained in projection vectors exposes features that can’t be easily noticed on the original data. That’s why the analysis of principal components scores contained in projections of WSN and ASN datasets may disclose differences and similarities between facial expressions among these races. One problem for analyzing those projections is that raw information of PC scores may be difficult to interpret because every projection has a common Eigenspace and the scores seems to be similar to those of different projection. Therefore, a complete evaluation of PC scores analysis has to cover comparisons of raw scores as well as visual information represented by them.

4.1 Visual Analysis

As mentioned in section 2.3, Drawface tool is used in this paper for achieving the visual analysis. Hence, we first calculate all the projections from both datasets, subsequently we divide them into its respective racial group (WSN and ASN) and facial expressions, for finally obtaining the average projection vector by each expression, this process is defined by:

$$AvgP_m = \frac{1}{L}\sum_{i=i}^{L} P_i, \qquad m = 1,2,\ldots,6 \qquad (1)$$

where *AvgP* is the average projection vector of the *m* expression, *P* is a single projection vector and *L* is the number of projection vectors from each expression (for our dataset *L*=40). Figure 5 shows caricaturazied faces obtained from the six *AvgP* of each race.

From Figure 5 we can observe that the most noticeable difference between WSN and ASN is found on the eyes region, however this difference is related with the physiology of the face instead of the activation of facial muscles associated with facial expressions. Therefore, the most significant difference from Figure 5 lied into the contrast of specific facial expressions. For instance, disgust and fear expressions stand as the most differentiable expression from WSN to ASN. Disgusted face from WSN race clearly shows a more closed mouth than that from ASN, in addition the movement shown by eyebrows region is entirely different. The fear expression presents the opposite situation on the mouth region, but the eyebrows of ASN face seems to be more raised than those from WSN. On the other hand, the rest of the basic expressions look very similar among the different racial groups, with the exception of surprised face of ASN which shows a physiological difference on the lips’ thickness.

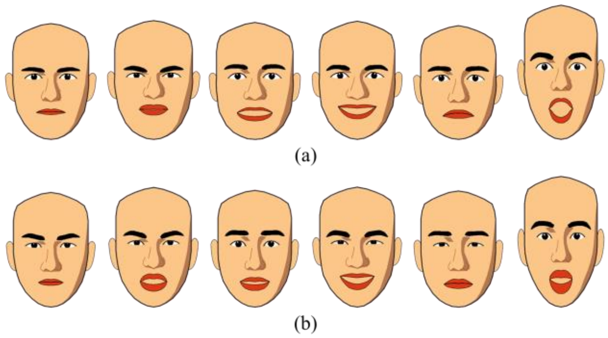

Fig. 5. Caricaturized faces of average projections of 6 basic expressions (from left to right, anger, disgust, fear, happiness, sadness and surprise) for (a) WSN and (b) ASN.

4.2 PC Scores Analysis

The analysis of principal component scores is focused on the first 10 PCs for each facial region. Don’t be confused with the real length of each projection vector (described in Section 2.2), indeed we just analyze 10 scores from the complete vector.

Thanks to the use of caricaturized faces, we can see that with only the first 10 PC scores of each facial part it is possible to represent a facial expression. For example, Figure 6 shows the caricaturized faces of disgust (WSN), Figure 6(a) was obtained by the whole average projection vector, moreover Figure 6(b) was obtained by using only the first 10 PCs per each facial region. It is possible to see that, even the different height of eyebrows, the differences from those caricatures are not significant and we can notice the expression displayed by them. Thus, the analysis of the first 10 PCs can provide reliable information.

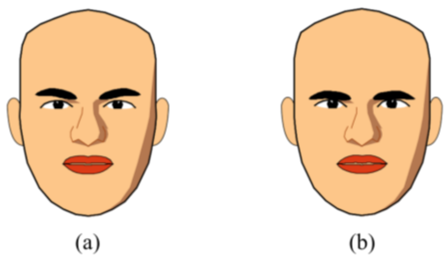

Fig. 6. Caricaturized faces of disgust (WSN).
(a) Obtained by the complete projection vector, (b) obtained by using 10 PCs per each facial region.

The results of the comparison analysis of PC scores confirm the observations gotten by the visual analysis of caricaturized faces, disgust and fear expressions represent the most diffident values among WSN and ASN projections.

Table 1 presents the scores of the most relevant facial regions for disgust expression (eyebrows, lips and nose). It is easy to notice that all the scores differ among the racial groups, especially those for nose and lips.

Table 1. PC scores of average projection of disgust.

	Eyebrows		**Lips**		**Nose**	
	WSN	**ASN**	**WSN**	**ASN**	**WSN**	**ASN**
PC1	1.85	0.23	6.13	-12.73	-0.38	2.05
PC2	-2.83	-0.88	1.13	21.78	39.48	17.70
PC3	-4.75	3.28	-3.20	-5.10	16.88	8.58
PC4	3.20	1.43	0.98	7.55	11.38	-16.63
PC5	9.80	-18.08	-2.43	-5.93	2.90	-0.53
PC6	10.78	-4.13	14.35	7.13	4.68	-5.48
PC7	-8.90	-8.58	1.55	-3.40	2.40	4.65
PC8	10.88	-0.13	-7.35	7.13	3.30	-7.63
PC9	-8.75	-8.68	9.30	7.60	3.70	-25.93
PC10	-9.85	13.88	-7.73	-1.78	24.53	6.78

On the other hand, Table 2 presents scores for anger, one of the expressions which looks very similar on a visual way. From this Table we can notice that most of the scores are similar but still have some differences, especially for the nose region. Therefore, we can point out that even the expressions look similar among the different facial groups, there exists a certain degree of difference.

Table 2. PC scores of average projection of anger.

	Eyebrows		**Lips**		**Nose**	
	WSN	**ASN**	**WSN**	**ASN**	**WSN**	**ASN**
PC1	4.65	3.65	20.18	20.20	10.40	-0.13
PC2	0.60	4.65	-5.65	2.73	19.23	-0.98
PC3	-8.08	-4.60	-6.45	13.60	13.40	-1.43
PC4	13.35	1.70	-20.55	-20.93	14.58	7.53
PC5	19.55	8.73	-5.93	-5.43	-11.40	-3.55
PC6	13.43	9.33	16.75	10.88	-1.70	-9.73
PC7	4.03	10.68	4.00	0.03	-2.13	-2.98
PC8	10.55	14.68	4.80	0.25	-0.03	-16.25
PC9	-2.70	-19.53	-12.08	-0.68	10.73	-18.43
PC10	-18.55	-15.03	-0.85	0.08	14.10	-1.53

5. CONCLUSION AND FUTURE WORK

An analysis of the differences between Western and East-Asian expressive faces was presented in this paper. It was carried out by handling 163 facial feature points and based on PCA application. In the evaluation section we presented a comparison of principal component scores qualitatively and quantitatively, concluding that the most relevant differences from Western and East-Asian faces fall in the expressions of disgust and fear, especially for the regions of eyebrows, lips and nose.

In summary, based on our experiment, we can say that the way of expressing disgust and fear from Westerns is different than that from East-Asians. However, in order to find out all the differences between those racial groups more issues have to be addressed, like the effect of the static structure of faces as well as the effect of wrinkles and texture information from the face. Therefore, this paper presents the beginning of one way for analyzing the form of expressing faces for different racial groups. In addition, we can conclude that the use of principal component scores is a powerful tool for this analysis.

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