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The Human Facial Expression Classification Using the Center Kernel Subspace based the Ridge Regression

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Abstract: The facial expression classification has been implemented on many devices. However, many researchers have conducted the research to improve the classification rate. This research has developed the algorithm to enhance the classification rate on the facial expression field. The proposed method is divided into five primary processes, which are, the first, create the center kernel subspace-based the ridge regression. Secondly, create five scales and eight orientations by using Gabor Filter Bank. The third is to obtain the new signal by using Two-dimensional-Fast Fourier Transform. Fourth, the results are used to build the feature space. It is conducted by the ridge regression of center kernel function. The last process, the primary features can be generated by multiplication between the center kernel and the Eigenvalue. The expression classification can be obtained by using the Mahalanobis method. The proposed method has been evaluated on JAFEE facial expression image database. Experimental shows that the classification rates for the first until the last scenarios are 83.33, 84.03, 86.61, 87.23, 87.24 and 89.79% respectively.

Keywords: Gabor Filter, Two Dimensional Fourier Transform, Facial Expression, The Ridge Regression, Center Kernel

Introduction

Many researchers have developed biometrics research field to improve the previous research. The results of the research have been implemented for many applications, such as motion detection, face detection, face recognition, finger recognition and palm recognition. However, the results of research are necessary to be improved, especially computational problem.

High dimensional of the training and the testing sets will effect on the high cost (Zhao and Pietikeinen, 2007; Tian *et al*., 2001). Therefore, it is necessary to conduct dimensionality reduction to the training and the testing sets.

Many algorithms have been implemented for dimensionality reduction, which are based on appearance (Shih *et al*., 2008; Wright *et al*., 2009; Martinez and Kak, 2001; Yang *et al*., 2004; Li and Yuan, 2005; Muntasa, 2014; 2015a; 2015b; Zhang and Zha, 2004; Sanguinetti, 2008), geometrical (Muntasa *et al*., 2012; Rizvandi *et al*., 2007; Cootes *et al*., 2000) and hybrid (Cootes *et al*., 2000; Tang and Wang, 2003).

Several cases based on appearance method often produce the singular matrix. If it occurred, the Eigenvalue and Eigenvector could not be determined. Although, the singular value decomposition can be used to overcome it. However, appearance based also has another limitation, which produces the global features. In fact, the local characteristics are also necessary as the dominant feature of an object. Inability to separate nonlinearly features is also the weakness of an appearance-based method.

In this research, a kernel-based method is proposed. It is utilized to transform from input into the feature space. In this case, the center kernel is introduced. It is conducted to overcome inability appearance based method to separate random features. Furthermore, Gabor Filter Bank is utilized to normalize the object shifting by using five scales and eight orientations.

To reduce the high dimensionality, Two-Dimensional Fast Fourier Transform is proposed to overcome it. The results of dimensionality reduction as primary features, they will be measured by using Mahalanobis method.

Furthermore, the remaining of this paper will be organized as follows. Section II consists of the proposed method. The similarity measurement using Mahalanobis method is written in section III. Finally, the experimental results have been reported and analyzed in section IV. The last section contains conclusion of experimental results.

Research Method

In this proposed method, an image is represented by using $f(x, y)$. In this case, x and y variables represent an axis and an ordinate position, whereas f depicts the gray scale of an image. In general, it can be mathematically written:

$$f(x,y) \mid x \in \{1,2,3,\cdots,H\},\quad y \in \{1,2,3,\cdots,W\},\quad f(x,y) \in \{1,2,3,\cdots,255\} \tag{1}$$

Furthermore, the original image as Equation (1) is processed by using five scales and eight orientations as seen in the Gabor Filter equation:

$$\mathrm{g}(\mathrm{x},\mathrm{y};\lambda,\theta,\psi,\sigma,\lambda) = \exp(\beta)\exp(\mathrm{i}\chi) \tag{2}$$

$$\mathrm{g}(\mathrm{x},\mathrm{y};\lambda,\theta,\psi,\sigma,\lambda) = \exp(\beta)\cos(\chi) \tag{3}$$

$$\mathrm{g}(\mathrm{x},\mathrm{y};\lambda,\theta,\psi,\sigma,\lambda) = \exp(\beta)\sin(\chi) \tag{4}$$

The β and χ values represent mathematics equation as seen follows:

$$\beta = -\frac{(x')^2 + \gamma^2 (y')^2}{2\sigma^2} \tag{5}$$

$$\chi = \left(2\pi \frac{\mathrm{x}'}{\lambda} + \psi\right) \tag{6}$$

The values of x' and y' can be explained in the following equation:

$$x' = x\cos\theta + y\sin\theta \tag{7}$$

$$y' = -x\sin\theta + y\cos\theta \tag{8}$$

Figure 1 represents the real part and Fig. 2 depicts the imaginary part by using five scales and eight orientation of the Gabor Filter.

Furthermore, the results of the Gabor Filter will be utilized as image input on the Two-Dimensional Fourier Transform as shown on the following equation:

$$F(kx,ky) = \sum_{jx=1}^{ny-1}\sum_{jy=1}^{nx-1} e^{-i\theta} * f(jx,jy) \tag{9}$$

In this case, the value of θ can be written as follows:

$$\theta = \frac{2\pi}{nx} * kx * jx + \frac{2\pi}{ny} * ky * jy \tag{10}$$

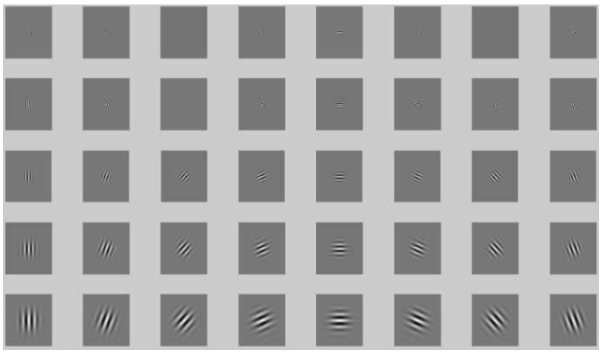

Fig. 1. The real part of Gabor filter

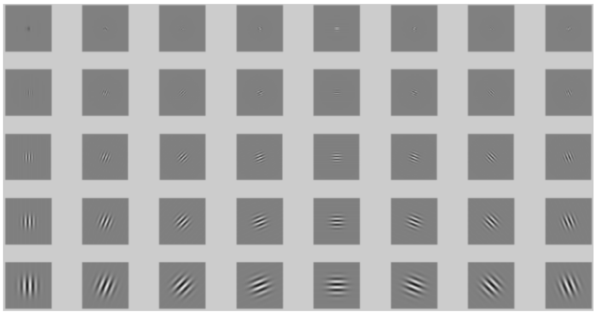

Fig. 2. The imaginary part of Gabor filter

To obtain the center kernel value, necessary to use the kernel center by using the following equation:

$$K_{centre} = K - I_3 * K - K * I_3 + I_3 * K * I_3 \tag{11}$$

$$I_3 = I.* H_I \tag{12}$$

Variable of K depicts the polynomial kernel of Equation 11. The identity matrix and its height are represented by using I and H. To obtain the ridge regression value; it is necessary to calculate the values of W and ς as shown in equation:

$$R_r = \frac{K_{centre} * K_{centre} + \zeta * I}{K_{centre} * W * K_{centre}} \tag{13}$$

The value of W and ς depict the auxiliary function and the small value of the ridge regression as seen on the following function:

$$\zeta = 10^{-\min(\mathrm{K}_{\mathrm{centre}})} \tag{14}$$

The Eigenvalue (λ) and vector (Λ) can be computed by using *singular value decomposition* based on Equation 13 and 14. The training features can be obtained by multiplication between square root of the Eigenvalue and the center kernel:

$$Fea_{tran} = \alpha * K_{centre} \quad (15)$$

$$\alpha = \sqrt{\sum_{i=1}^{n} \lambda_i} \quad (16)$$

To obtain the testing features, it is necessary to calculate the value of K_{ct}:

$$K_{ct} = K - \left(I_3 * (I_3)^T\right) * T_f - \upsilon \quad (17)$$

$$\upsilon = \frac{K}{\alpha} * \left(I_3 * (I_3)^T\right) + \left(I_3 * (I_3)^T\right) * K * \left(I_3 * (I_3)^T\right) \quad (18)$$

The testing feature can be modeled simplify as seen in the following:

$$Fea_{test} = \alpha * K \quad (19)$$

Similarity Measurement Using Mahalanobis

Furthermore, the results of feature extraction will be measured between testing object and training object. In this case, the Mahalanobis method is used to obtain the biggest probability as shown:

$$d = \sqrt{\left(\left(\bar{X}_j - \bar{Y}_j\right) C_{j,j}^{-1} \left(\bar{X}_j - \bar{Y}_j\right)^T\right)} \quad (20)$$

The value of C represents X and Y covariance as seen on the following equation:

$$C_{j,j} = \frac{m}{m+p}\left(CX_{j,j}\right) + \frac{p}{m+p}\left(CY_{j,j}\right) \quad (21)$$

$$CY_{j,j} = (Y_{i,j} - \bar{Y}_j)^T (Y_{i,j} - \bar{Y}_j) \quad (22)$$

$$CX_{j,j} = (X_{i,j} - \bar{X}_j)^T (X_{i,j} - \bar{X}_j) \quad (23)$$

Experimental Results and Analysis

One of the face image databases for facial expression recognition is the Japanese Female Facial Expression or well known as the JAFFE. The proposed method was evaluated by using the JAFFE image database as the experimental data set. It has captured 213 times (Lyons *et al*., 1998), it consists of seven expressions. Distribution of the expression of JAFFE face image database can be seen in Table 1. A sample of JAFFE face image database can be shown in Fig. 3.

In this research, the proposed method has been evaluated by conducting the six times experiment.

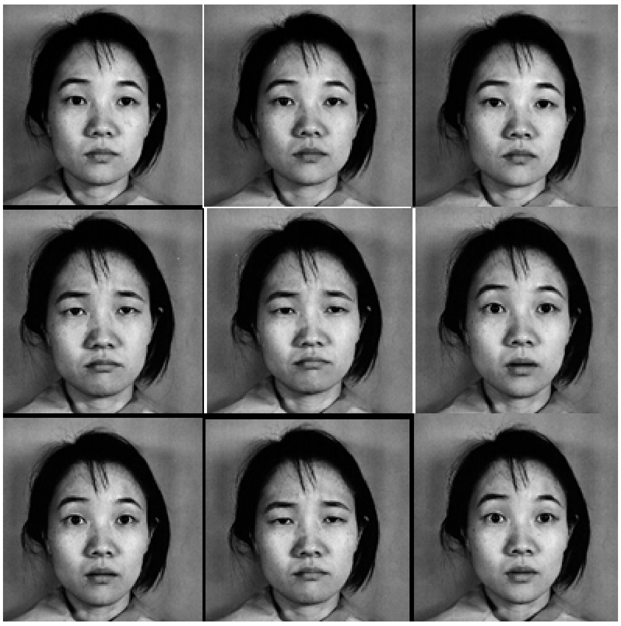

Fig. 3. Sample of the Facial Expression from JAFEE

Table 1. The JAFFE face image database distribution

Expression	Number of image sets
Neutral	30
Happiness	31
Sadness	31
Surprise	30
Anger	30
Disgust	29
Fear	32

Table 2. Experimental results of the first scenario

Expression	Number of training set	Number of testing set	Recognition rate (%)
Neutral	12	18	83.33
Happiness	13	18	88.89
Sadness	13	18	83.33
Surprise	12	18	83.33
Anger	12	18	83.33
Disgust	11	18	83.33
Fear	14	18	77.78
Recognition average (%)			83.33

Because every expression has some distribution difference of the data sets, a lot of training sets for each expression is also different. The experimental results for each scenario can be seen in Table 2-7.

On the first experiment, the testing set used is 18 images for each expression, whereas the remaining of them is used as training sets. The experimental results show that the highest error occurred on the fear expression image, which is four times error. The highest recognition rate occurred on a happiness expression

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image as seen in Table 2. On the first experiment, the recognition average obtained is 83.33%

Table 3 demonstrated the experimental results of the second scenario. Seventeen images were used as the testing sets and the remaining of them were used as the training sets. The experimental results show that the lowest recognition rate has occurred on the fear image expression, fourteen images were correct recognized. The highest recognition is occurred on the neutral, anger and sadness expressions, which are sixteen of eighteen images. The recognition average of the second experiment is 84.03.

On the third scenario, some training sets have been increased one for each expression so that the number of testing sets also decreases one. Table 4 shows that the additional of the training sets has increased the recognition average, though, on the certain expressions. The recognition rate of the third experiment is 86.61. The recognition rate is also better than the first and the second experiment results.

The similar condition is also occurred on the fourth, fifth and sixth scenarios as seen in Table 5. The experimental results have also shown the improvement of recognition average. It is proportional to the increasing of the training sets used.

On the fifth scenario, the experimental results show that recognition rate almost has not increased. Its difference is only 0.01%. In detail, the experimental results of the fifth scenario can be seen in Table 6.

Table 3. Experimental results of the second scenario

Expression	Number of training set	Number of testing set	Recognition rate (%)
Neutral	13	17	88.24
Happiness	14	17	82.35
Sadness	14	17	88.24
Surprise	13	17	82.35
Anger	13	17	88.24
Disgust	12	17	82.35
Fear	15	17	76.47
Recognition average (%)			84.03

Table 4. Experimental results of the third scenario

Expression	Number of training set	Number of testing set	Recognition rate (%)
Neutral	14	16	93.75
Happiness	15	16	87.50
Sadness	15	16	93.75
Surprise	14	16	81.25
Anger	14	16	87.50
Disgust	13	16	81.25
Fear	16	16	81.25
Recognition average (%)			86.61

Table 7 explained the experimental results of the last scenario. On the last scenario, the proposed method produced the recognition average 89.79%. The increasing of recognition rate is 2.55% from the fifth scenario. It shows that the more number of training sets used, the more recognition average achieved.

Based on the first until the last scenario, the experimental results can be shown that the number of training sets used is proportional increasing of recognition average as seen in Fig. 4. Increment of the significant recognition average is not found for all experiments, but the increment of the recognition average is occurred for each experimental. The usage of the training sets has influenced recognition average obtained.

The experimental results were also compared with another paper, which is Local Binary Patterns (Ojala *et al*., 2002). The Local Binary Patterns method has produced 85.57%. It shows that the Local Binary Pattern has outperformed to the proposed method for the first and the second scenarios. But the proposed method has outperformed for the third, the fourth, the fifth and the sixth scenarios.

Table 5. Experimental results of the fourth scenario

Expression	Number of training set	Number of testing set	Recognition rate (%)
Neutral	16	14	92.86
Happiness	16	15	86.67
Sadness	16	15	86.67
Surprise	16	14	92.86
Anger	16	14	85.71
Disgust	16	13	84.62
Fear	16	16	81.25
Recognition average (%)			87.23

Table 6. Experimental results of the fifth scenario

Expression	Number of training set	Number of testing set	Recognition rate (%)
Neutral	17	13	92.31
Happiness	17	14	85.71
Sadness	17	14	85.71
Surprise	17	13	92.31
Anger	17	13	84.62
Disgust	17	12	83.33
Fear	17	15	86.67
Recognition average (%)			87.24

Table 7. Experimental results of the sixth scenario

Expression	Number of training set	Number of testing set	Recognition rate (%)
Neutral	18	12	91.67
Happiness	18	13	84.62
Sadness	18	13	92.31
Surprise	18	12	91.67
Anger	18	12	91.67
Disgust	18	11	90.91
Fear	18	14	85.71
Recognition average (%)			89.79

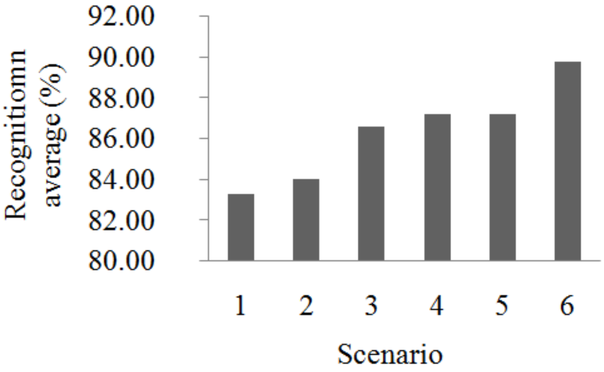

Fig. 4. The recognition average of proposed method

Conclusion

The proposed method, the center kernel subspace-based the ridge regression can be used as feature extraction for facial expression recognition. The experimental results show that the more training set used, the higher recognition rate was produced. It shows that the results of recognition depend on the training set used. However, there are some images misclassifications. They are caused by the similarity between the testing and the training images, where the similar images are not in a class. Misclassification can be improved by conducting the collaboration of method.

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Ethics

The paper is the original research results of the author. It did not contain plagiarism contents. This paper did not also published by another publisher.

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