The Fifteenth International Symposium on Artificial Life and Robotics 2010 (AROB 15th '10),
B-Con Plaza, Beppu,Oita, Japan, February 4-6, 2010

A Study of Dimension Reduction of Gabor Features from Different Facial Expressions

Rosdiyana Samad and Hideyuki Sawada

Department of Intelligent Mechanical Systems Engineering, Faculty of Engineering, Kagawa University,
2217-20 Hayashi-cho, Takamatsu, Kagawa, 761-0396, Japan.
Tel: +81-(0)87-864-2324 Fax: +81-(0)87-864-2369
s09d501@stmail.eng.kagawa-u.ac.jp, sawada@eng.kagawa-u.ac.jp

***Abstract*:** Facial expressions are an important channel of nonverbal communication. Currently, many facial expression analysis or recognition systems have been proposed. In this paper, a study of dimension reduction of Gabor features from different facial expressions is presented. Principle Component Analysis (PCA) is used as dimension reduction method. The experiment is conducted by using samples of face image for eight subjects. There are six facial expressions; anger, fear, happy, neutral, sadness and surprise are used in this study. In this experiment, we use different poses and head postures of each subject. Experiment results demonstrated the reduced dimensions of Gabor features could be effectively used in the next processing for recognizing facial expressions.

Keywords: **facial expression, Gabor features, dimension reduction, PCA.**

I. INTRODUCTION

Nowadays, computer-based applications become more sophisticated and are increasingly involved in our daily life. Human-computer interface is one of the outcomes that have been developed to fulfill human needs in facilitating some task. Over the last decade, face detection and facial expression recognition have become an active research area that finds potential applications for human-computer interfaces, talking heads, image retrieval and human emotion analysis [1]. In recent years, numerous algorithms for face detection and facial expression recognition have been proposed.

Moore and Bowden [2] wrote in their literature review, the earliest work on facial expression recognition was introduced by Ekman, and it was called Facial Action Coding System (FACS). FACS provided a prototype of the basic human expressions and allowed researchers to study facial expressions based on anatomical analysis of facial movement. In other research, Ma and Khorasani [3] applied two-dimensional discrete cosine transform (DCT) over the entire face image to extract the facial feature, and developed one-hidden-layer feed forward neural network to recognize the facial expressions. Littlewort et al. [4] proposed a method to extract the dynamics of facial expression automatically from video. In this study, Gabor energy filter was used in feature extraction technique and then three different classifiers were used to classify the facial expressions into 7 classes (neutral, anger, disgust, fear, joy, sadness, surprise). These three classifiers were AdaBoost, Supervised Vector Machine (SVM) and Linear Discriminant Analysis (LDA). At the end of this experiment, they had examined the performance of the classifier.

Deng et al. [5] proposed a facial expression recognition system based on local Gabor filter banks with the selected part of frequency and orientation parameters. Two stages of feature compression method were employed to select and compress the Gabor features. First stage was PCA and then followed by LDA. The recognition of facial expression was done by applying minimum distance classifier. Loh, Wong & Wong [6] developed an e-learning system that used facial expression recognition. They also applied Gabor wavelet for facial feature extraction and back propagation neural network for the classification.

In this paper, a study of dimension reduction of Gabor features from different expressions is presented. We selected 6 facial expressions in this work, which are sadness, happy, anger, fear, surprise and neutral.

II. METHODOLOGY

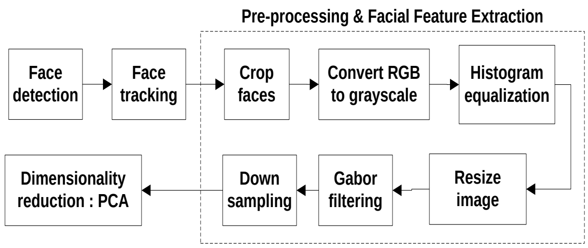


Fig.1. Block diagram of the proposed method.

Figure 1 shows the block diagram of our work. In this paper we briefly present a face detection method, and then explain in detail the facial feature extraction technique.

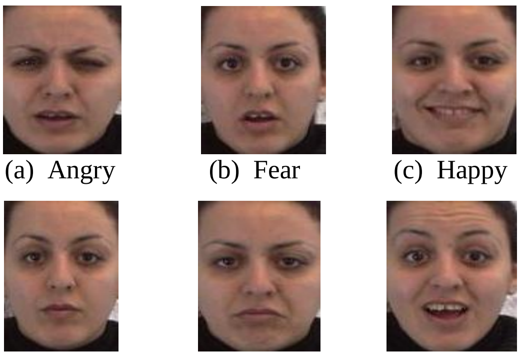
1. Face detection & tracking

Haar-like features and AdaBoost algorithm were used in the face detection phase. This technique was introduced by Paul Viola and Micheal Jones[7], and then was improved by Reiner Lienhart[8]. Following the algorithms, face tracking technique was added which enabled the face detector to track the moving face. This technique is called Camshift, otherwise known as Continuously Adaptive Mean Shift. At this stage, we used 700 positive samples (patch of human face) and 437 negative samples (background images or non-face) to train AdaBoost algorithm.

2. Pre-processing & facial feature extraction

In this experiment we used images from eight subjects that were selected from FEEDTUM [9] database. Multiple images of six facial expressions with different poses and head postures were taken from each subject. Total number of sample images was 943.

Firstly, at the pre-processing stage we cropped the face images manually in order to remove the background information and have only face details. Figure 2 shows samples of face image that were used in this study.



(a) Angry (b) Fear (c) Happy
(d) Neutral (e) Sadness (f) Surprise

Fig.2. Image samples for different facial expressions.

Fig.3. Output image of histogram equalization.

At the beginning, all sample images were in RGB and then we converted them into grayscale. The grayscale images outcome from the conversion were poor because of lacking contrast; thus we employed the histogram equalization on the images. As a result, the images were enhanced and the face detail was improved. Figure 3 shows the output image of histogram equalization.

The Gabor filter represents the properties of spatial localization, orientation selectivity and spatial frequency selectivity. The Gabor filter can be defined as:

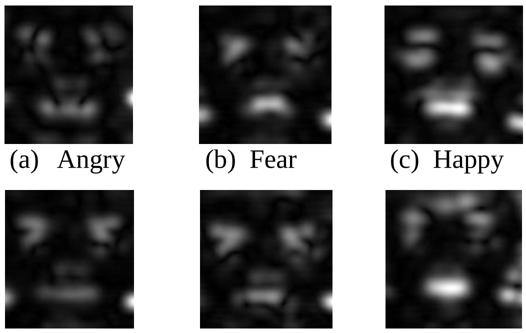
$$\psi(z) = \frac{k_{u,v}^2}{\sigma^2} \exp\left(-\frac{k_{u,v}^2 z^2}{2\sigma^2}\right)\left[\exp\left(ik_{u,v}z\right) - \exp\left(-\frac{\sigma^2}{2}\right)\right] \quad (1)$$

where z = (x,y), u and v define the orientation and scale of the Gabor wavelets, respectively [10]. $k_{u,v}$ is defined as follows:

$$k_{u,v} = k_v e^{i\Phi} \quad , \qquad (2)$$

where $k_v=k_{max}/f^v$ and $\Phi u = \pi u/8$. k_{max} is the maximum frequency, and f is the spacing factor between kernels in the frequency domain.

In this experiment we applied Gabor filter with one scale (v=1) and one orientation (u= 4), with the parameters $\sigma = 2\pi$, $k_{max} = \pi/2$ and $f=\sqrt{2}$. The Gabor representation of an image, which is called the Gabor image, is produced from the convolution of the image with the Gabor kernels as defined by Eq.(1). For each image pixel, it produces two Gabor parts: the real part and the imaginary part. Subsequently, these two parts were transformed into two kinds of Gabor features: magnitude and phase. In this study we used magnitude features to represent the facial Gabor features. Figure 4 shows the Gabor magnitude responses for each expression (anger, fear, happy, neutral, sadness and surprise) derived from the images shown in Figure 2.



(a) Angry (b) Fear (c) Happy
(d) Neutral (e) Sadness (f) Surprise

Fig.4. Gabor magnitude responses for different facial expressions.

The Gabor image size was 120x120 pixels, which produced 14,400 feature vectors. The numbers of the features were too many therefore we needed to reduce the image size so the number of features would be smaller. To get the smaller size of images we performed Gaussian pyramid down sampling [10]. This method reduced the size of an image by a factor of 2. The down sampling method performs a Gaussian smooth using 5x5 Gaussian kernel and then removes every other line from an image. The image result obtained from the down sampling was 60x60 pixels. The output images still large, and again, we downsized the images into 30 x 30 pixels so that we could have only 900 features.

3. Dimensionality reduction

As mentioned in the previous section, the final output image size was 30x30 pixels that produced 900x1 feature vectors. We used these feature vectors as input data to the Principle Component Analysis (PCA). PCA is a way of identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences [11]. The other main advantage of PCA, it is able to reduce the number of dimensions without much loss of information. Besides, PCA is a powerful tool for analyzing high dimension data, since graphical representation for high dimension data is not available. In this paper, we used PCA to reduce the number of feature vectors so it also will cut down the computation time for the classification in the next stage.

At this stage, we subtracted the mean from each of the data. The mean subtracted is the average across each dimension, then the covariance matrix was calculated. After that, eigenvectors and eigenvalues were calculated based on covariance matrix that has been computed before. Next, we selected 20 most significant eigenvalues to get the eigenvectors. Finally, the eigenvectors were projected onto subspace.

III. EXPERIMENTAL RESULTS & DISCUSSION

In this study, Gabor filter with horizontal orientation was selected because it produced discriminative Gabor features better than other orientations. In addition, by using only one orientation it helped to reduce the computational complexity of Gabor features extraction. As a result, facial features, such as eyes, nose, mouth and wrinkles at each expression (as shown at Fig. 4) would give different appearance. The variability in the underlying Gabor magnitude response of facial images corresponds to differences among different facial expressions. In the PCA, the eigenvector indicates the direction in which the data greatly distributed. The direction of maximum separation is called the first component of a dataset. We plotted the first, second and third component of dataset and it shows the separation of the data.

From the observation of the scatter plots, the facial expression data for each subject were grouped with one another but some of them were slightly overlapped with the different group of expressions. It shows data in the tight cluster have least variability while data from separated cluster have the greatest variability (as shown at Fig. 5(a)). From the results, we found that our data were separated into each type of facial expression. Facial expressions data for subject number 5, 6 and 7 had slightly scattered and overlapped. At these figures, the overlapped data were the expressions of sadness and neutral. This is because the sadness and neutral expressions for the subject is nearly similar which is shown in Figure 6.

IV. CONCLUSION

In this paper, a study of features extraction by using Gabor filter and dimension reduction by PCA is carried out. The PCA was used to downsize the big number of Gabor features. The purpose of the dimension reduction is not only to cut down the dimension, but also to reduce the computational time. Fast processing time will give advantage to the next process which is the classification of different facial expressions that we will develop later. Results obtained from the scatter plots show that facial expression data were grouped with one another according to the type of expressions. From the detailed analysis of data plots, the compressed Gabor features could be effectively used in the next processing for recognizing facial expressions.

REFERENCES

[1] Fasel B and Luettin J (2003), Automatic facial expression analysis - a survey. Pattern Recognition Vol.36, pp. 259-275

[2] Moore S and Bowden R (2007), Automatic facial expression recognition using boosted discriminatory classifiers. Computer Science Vol. 4778, pp.71-83

[3] Ma L & Khorasani K (2004), Facial expression recognition using constructive feed forward neural network. IEEE Trans. on Systems, Man & Cybernetics Vol. 34, pp.1588-1595

[4] Littlewort G et al (2004), Dynamics of facial expression extracted automatically from video. Proc. of Computer Vision and Pattern Recognition Workshop, pp. 80-90.

[5] Deng H B et al (2005), A new facial expression recognition method based on local Gabor filter bank and PCA plus LDA. Information Technology Vol. 11, pp. 86-96

[6] Loh, Wong & Wong (2006), Facial expression recognition for e-learning system using Gabor wavelet & neural network. Proc. of 6th IEEE Int. Conf. on Advanced Learning Technology, pp. 523-525

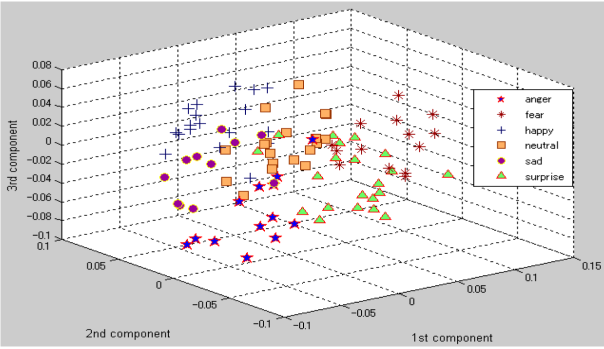
[7] Viola P & Jones M (2001), Rapid object detection using a boosted cascade of simple features. Computer Vision and Pattern Recognition Vol.1, pp.511-518

[8] Lienhart R & Maydt J (2002), An extended set of haar-like features for rapid object detection. Proc. of IEEE Int. Conf. on Image Processing, pp.900-903

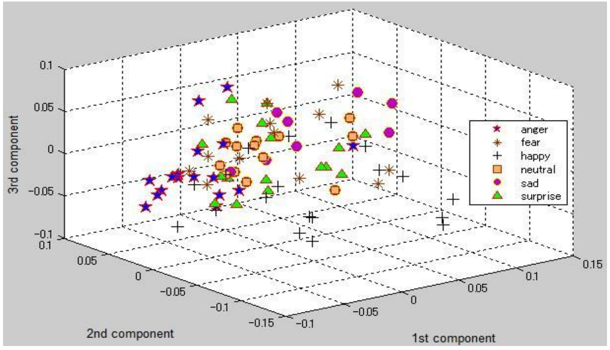
[9]Facial Expressions & Emotion Database Technische Universitat Munchen (FEEDTUM) http://www.mmk.ei.tum.de/~waf/fgnet/feedtum.html

[10] Lee TS (1996), Image representation using 2D Gabor wavelets. IEEE Trans. On Pattern Analysis & Machine Intelligent Vol.18, pp. 959-971

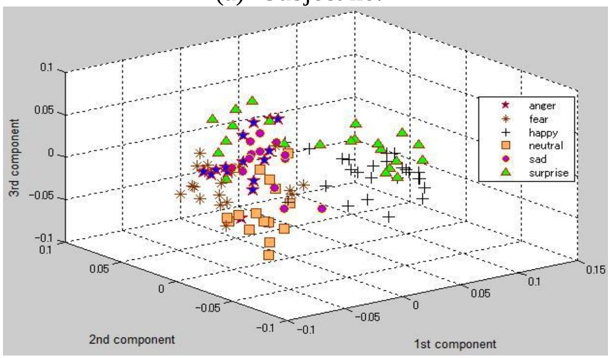
[11] Smith LI (2002), A tutorial on principle component analysis. Cornell University USA, pp.2-2



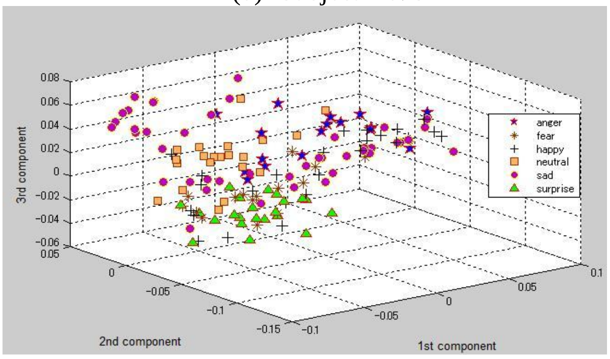
(a) Subject no.



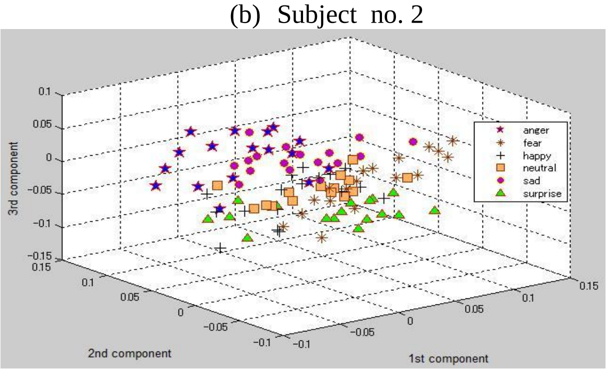
(d) Subject no. 5



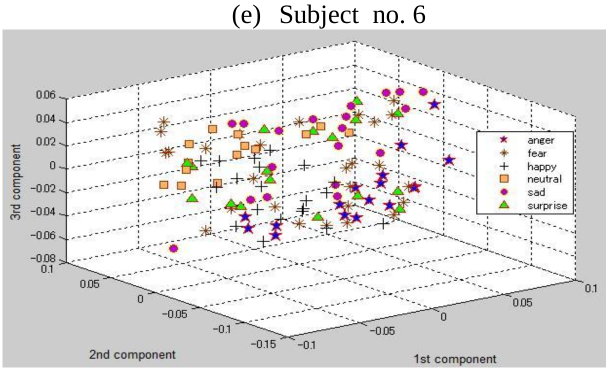
(b) Subject no. 2



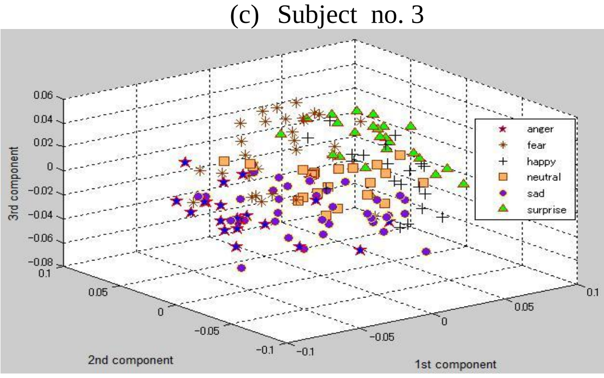
(e) Subject no. 6



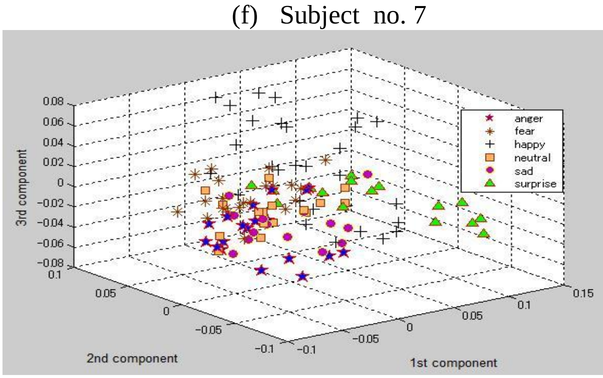
(c) Subject no. 3



(f) Subject no. 7



(d) Subject no. 4



(h) Subject no. 8

Fig. 5 3D Plots of facial expression data from 8 subjects.

Fig.6. Facial expressions of sadness and neutral that seemed almost the same.