2010 Fourth Pacific-Rim Symposium on Image and Video Technology

A Novel Facial Expression Recognition based on the Curvelet Features

Juxiang Zhou Yunqiong Wang[a] Tianwei Xu
College of Information
Yunnan Normal University
Kunming, China
zjuxiang@126.com,wyunqiong@sina.com.cn,xutianwei@ynnu.edu.cn

Wanquan Liu
Dept. of Computing
Curtin University
Perth WA, Australia
w.liu@curtin.edu.au

Abstract—Curvelet transform has been recently proved to be a powerful tool for multi-resolution analysis on images. In this paper we propose a new approach for facial expression recognition based on features extracted via curvelet transform. First curvelet transform is presented and its advantages in image analysis are described. Then the coefficients of curvelet in selected scales and angles are used as features for image analysis. Consequently the Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA) are used to reduce and optimize the curvelet features. Finally we use the nearest neighbor classifier to recognize the facial expressions based on these features. The experimental results on JAFFE and Cohn Kanade two benchmark databases show that the proposed approach outperforms the PCA and LDA techniques on the original image pixel values as well as its counterparts with the wavelet features.

Keywords-Facial expression recognition, PCA, LDA, Curvelet transform, Wavelet.

I. INTRODUCTION

Facial expression recognition, as one of the important topics in pattern recognition and computer vision, has broad applications in fields of human-computer interaction, psychological behavior analysis, image understanding etc. [2][3][20]. In recent years, many researchers have done a lot of research on this topic with a variety of methods [7][10][20][21], and some promising results have been achieved. However, there are still some issues not well addressed properly in the exiting literature, such as robustness and reliability related to impacts of illumination, posture changes, partially occlusions and low resolutions [4][5][23]. Therefore, we still need to find better features/classifiers that are more robust and with better discriminative capability. Up to now, many feature extraction approaches have been proposed; including the subspace based holistic feature extractions and the local appearance feature extractions. In the former category, typical ones include the well-known PCA and LDA. The latter category includes the Gabor and wavelets approaches [7][16][24][25].

With the maturity of the wavelet theory in last two decades, wavelet transform has attracted much more attention in computer vision areas including facial expression recognition and face recognition [11][12][26]. Though many results have been achieved with wavelet transform in signal reconstruction, image analysis, facial expression recognition, etc, the wavelet transform has significant limitations in representing image edges as reported recently in [13][27]. This is mainly due to a fact that wavelet transform can only reflect the singularity of "dot" positions and specialty, but difficult to express characteristics for curves and edges. In image processing applications, a lot of facial information is included in edges, while wavelet transform can only reflect the specialty of "across" edges, but not "along" the edges since there is not enough directional information in wavelets [6][14][27]. Moreover, the basis of wavelet applied in image processing is isotropous, which implies that it is unable to express directions of image edges accurately, also it cannot achieve sparse representation of images. So, it's difficult to represent the important characteristics of facial contour and curve features using the wavelet. In order to overcome these limitations of wavelet transform, a new multi-scale analysis tool-Curvelet transform, is proposed recently [13]. Curvelet transform has good time-frequency localization characteristics, and can describe gradually to any details for an object and it can characterize the facial local information effectively.

Though there are several basic results on image denoising, face recognition and palm print recognition using the curvelet features [9][19][17][28]. To best of our knowledge, there is still no research on facial expression recognition with curvelet transform until now. In this paper we will investigate this problem. We first propose a new feature extraction method based curvelet coefficients including the low frequency, the high frequency and detailed information parts, and then we select the curvelet coefficients of low frequency part and detailed information parts as possible features. Then we use the PCA and LDA to reduce the dimensions of these features and finally use the nearest neighbor classifier for facial expression recognition. The results of the extensive experiments on JAFFE [8] and Cohn Kanade [1] two databases show that the proposed method can achieve higher recognition rates compared to the original PCA and LDA as well as the performances based on wavelet coefficients. More importantly, the experimental results also illustrate that the detail information part in

a) The correspondence author.

978-0-7695-4285-0/10 $26.00 © 2010 IEEE
DOI 10.1109/PSIVT.2010.21

curvelet transform can represent the image quite well and only its corresponding features can achieve the best recognition performance in several cases. This is an important indication for our future investigation in other applications with curvelet transform.

The structure of the paper is organized as follows. In section 2, we will describe the curvelet transform and its related progress. In section 3, we investigate the feature selection based on the curvelet transform coefficients and the facial expression recognition algorithm. In section 4, we will do extensive experiments on two benchmark datasets and analyze the results, and the conclusions are given in section 5.

II. Curvelet Transform

Candes and Donoho first proposed the curvelet transform based on the Ridgelet transform in 1999, i.e., the first generation of curvelet transform [14]. There are some successful applications for the first generation curvelet transform, which in fact uses a pre-processing step involving a special partitioning of phase-space followed by the ridgelet transform, which is applied to blocks of data that are well localized in space and frequency [6][13]. In order to make the implementations simpler, faster and less redundant, the second generation of curvelet transform is proposed in 2006 [13]. It's an effective analytical method for multi-resolution, band pass and directions that are considered as three important characteristics the "optimal" image representation should have from the perspective of biological point of view. Therefore, the curvelet transform has better representation capability than wavelet transform for image edges. The scale and angle segmentations in curvelet transform are shown in Figure 1. The coefficients in the wedge (represented in the shaded area in Figure 1) represent both angle and scale information as explained in [6][13]. Furthermore, the curvelet has the sparse property compared to wavelets in the sense that curvelet decomposition can approximate the original image better with less no-zero coefficients.

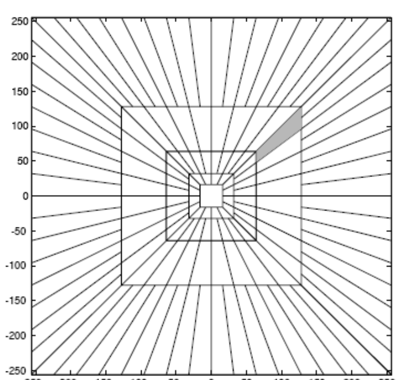

Figure 1. The scale and angle segmentation of Curvelet transform

In fact two different digital implementations are proposed for curvelets; one is based on the USFFT (Unequispaced Fast Fourier Transform) and the other is based on wrapping idea [13]. In this paper, we select the one with USFFT for implementation simplicity and the algorithm is described as follows [13].

Suppose that we have a two dimensional discrete function

$$f(t_1, t_2) \text{ with } 0 \le t_1, t_2 < n.$$

(1) Apply the 2D discrete Fast Fourier Transform and obtain the Fourier samples

$$\hat{f}[n_1, n_2],\ -n/2 \le n_1, n_2 \le n/2$$

(2) For each scale/angle pair (j, l), we resample $\hat{f}[n_1, n_2]$ and obtain the following sampled values

$$\hat{f}[n_1, n_2 - n_1 \tan\theta_l] \ \ for \ \ (n_1, n_2) \in p_j$$

where p_j is defined in [13].

(3) Multiply the interpolated object $\hat{f}$ with the parabolic window $\tilde{U}_j$ defined in [13] and obtain

$$\hat{f}_{j,l}[n_1, n_2] = \hat{f}[n_1, n_2 - n_1 \tan\theta_l]\tilde{U}_j[n_1, n_2]$$

(4) Apply the inverse 2D FFT to each $\hat{f}_{j,l}$, hence collecting the discrete coefficients $C^D(j, l, k)$.

Though there are some papers on face recognition with these curvelet features [17][19][27][28] and they all proved that better results can be achieved. Until now, to best of our knowledge, there is no results reported in the existing literature via using the curvelet features for facial expression recognition and we will investigate this problem in this paper.

III. Curvelet Feature extraction and Expression Recognition

PCA has been used successfully on wavelet decomposed images [15][22]. As addressed in [6][13][27], wavelets are only suitable for detecting singular points in an image and fail to represent curved discontinuities along edges. On the contrary, the curvelet transform can represent the curved changes. In image processing, the edges in an image represent significant information which can be used for representation and recognition [18]. One significant advantage of curvelet over wavelet is that curvelet includes the detailed information on edges. In this paper, we will select some features based on curvelet coefficients and use them for facial expression recognition.

A. *Curvelet decomposition*

After curvelet decomposition on a facial image, we will receive the coefficients corresponding to low frequency, detail information of different layers characterized by different scales and angles, and high frequency. In fact, the coefficients of low frequency can greatly reduce and represent the essential characteristics of a human face, and the detail layer coefficients can describe the important information of face from different scales and angles, and the coefficients of high frequency reflect the facial contour and rough curves. Figure 2 shows images represented by the curvelet coefficients of a face from JAFFE dataset.

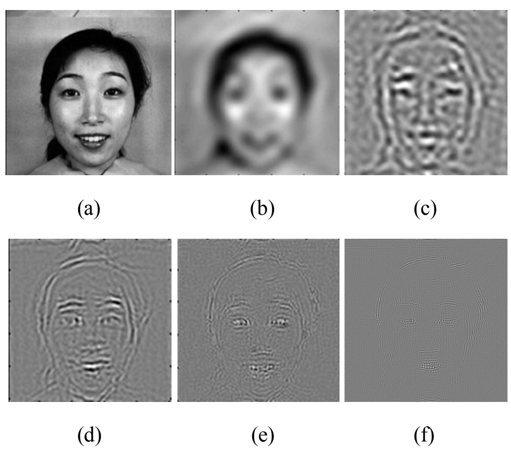

Figure 2. (a)-(f) are the original image, low frequency, detail 1, detail 2, detail 3 and high frequency parts respectively.

From these figures, we can find that the detail layers represent the image sketch quite well, and include much richer information than that in the low and high frequency parts for wavelets. This observation is further demonstrated in our experimental results in section 4.

In order to analyze the curvelet coefficients, we first require a face image's expression region with resolution nxn (n dyadic). Then the images are decomposed using the curvelet transform with scale $=\log_2(n)-3$. The inner layer is a coefficient matrix corresponding to the low frequency of 32x32, and the external layer is coefficient matrix for high frequency of nxn, and the middle parts are detailed layers. Every detailed layer is divided into four round angles, each of which is divided into several small directions. There is a coefficient matrix in every sub-angle. Most of the image energy is concentrated in the sub-band of low frequency after curvelet decomposition, decreasing gradually in the rest of layers [6]. In our proposed method, because the coefficients matrix of high frequency is large and contains a small of energy that goes against the training and recognition, we only select respectively the coefficient matrix for low frequency and coefficient matrices of the detail layers as possible expression features.

B. *Feature extraction*

For the curvelet, because the image used in latter experiment is 128x128 pixels, we conduct the curvelet decomposition in 4 scales. They are low frequency, first detailed layer with 32 directions, second detailed layer with 32 directions and high frequency respectively. For every sub-angle, there is a coefficient matrix of 16x22 or 22x16 at first detailed layer and 22x32 or 32x22 at second detailed layer. We select low frequency, first detailed layer with 4 and 8 directions, second detailed layer with 4 and 8 directions as the curvelet features respectively.

C. *Expression Recognition*

In comparison with the size of an original image, we can obtain small size coefficient matrix after curvelet transform. However, if we use these feature matrices directly, their dimensions are still very high. Therefore, in the stage of feature extraction, we first select the curvelet coefficients of different scales, then PCA and LDA are applied on the selected subbands, which further reduce and optimize the dimensions of image data. In classification stage, the kNN classifier is used for classification.

IV. EXPERIMENTAL RESULTS

A. *Datasets*

JAFFE database: The JAFFE database [8] contains 213 gray images (256x256) of individual human subjects with a variety of facial expressions. In this database, 10 different Japanese female performed seven prototypical expressions: *anger, disgust, fear, joy, sadness, surprise* and *neutral*. We choose three samples per facial expression for each subject, and a total of 210 images.

Cohn-Kanade database: The Cohn-Kanade database [1] contains video sequences of 97 subjects displaying distinct facial expression. We create a subset with 10 subjects for our experiments. All the subjects selected have six basic expressions: *anger, disgust, fear, joy, sadness* and *surprise*. From every sequence for each expression of a subject, we select the last four frames as static gray images (640x490). So there are 240 total images in all.

In JAFFE database, there are 30 samples for each expression. To verify the effectiveness of various methods with different numbers of training samples, we select randomly 10, 15, 20 and 25 images per expression for training, and the rest images are used for testing respectively. In Cohn-Kanade database, there are 40 samples for each expression. Similarly, we select training samples and testing samples with the above method.

B. *Preprocessing*

All images from above-mentioned two data sets are cropped with expression region only and normalized to 128x128 pixels with nearest-neighbor interpolation method. A few of cropped samples are shown in Figure 3 and Figure 4.

Figure 3. Cropped samples from JAFFE database

Figure 4. Cropped samples from Cohn-Kanade database

C. *Experiments*

In order to compare the performances based on the curvelet and wavelet coefficients, we extract respective decomposition coefficients in different frequency domains as features. Firstly, a 3-level wavelet decomposition using dauchebies 4 wavelet was performed for wavelet. The features we selected for such wavelet are low frequency at 2-level, compact high frequency at 2-level and 3-level, diagonal high frequency at 2-level and 3-level.

For every experiment with different selected features, the designed experiment is repeated 10 times, and the final recognition rate is the average accuracy with possible best dimension of PCA.

Experiment 1: PCA, LDA with appearance pixel values and curvelet features

In this section, we mainly compare the PCA and LDA performances by using the appearance pixel values and the curvelet features. The content of table 1 shows the respective performances with different numbers of training samples in JAFFE and Cohn-Kanade databases. One can find from table 1 that the PCA and LDA based on the curvelet features can achieve much better results.

One knows that the number of PCA dimensions usually affects the recognition rates as PCA works on the image pixel values. We further test the mentioned seven methods in table 1 with different PCA dimensions from 10 to 100 respectively when the number of training sample is 15. The result is shown in Figure 5.

We can see from Figure 5 that the increase of the PCA dimensions can't guarantee the improvement of the recognition rates accordingly. Also, PCA plus LDA based on the curvelet coefficients of low frequency can achieved better recognition rates in comparison to using the curvelet coefficients of detailed layers. Furthermore, it completely outperforms the PCA and LDA methods on image pixel values when using curvelet coefficients of low frequency and the first detailed layer.

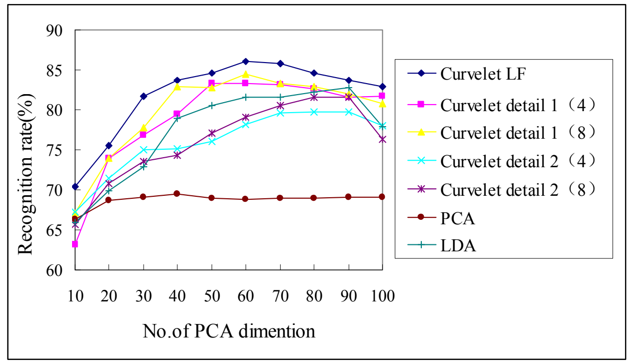

Figure 5. Recognition rate vs PCA dimension

Experiment 2: Wavelet via Curvelet Comparisons

In order to signal out the importance of curvelet transform over wavelet in facial expression recognition, we will design two schemes to compare the performances of LDA with extracted features from these two transforms. The first one is to compare the best individual performance for each component after curvelet and wavelet transforms. We have done all the experiments on face images for these two databases and the same conclusion is obtained, i.e., the curvelet will achieve better much results. We can refer to table 1 in the part of experiment 1 for curvelet results and next we just list the performance using the wavelet features with the different number of training sample similarly in table 2.

From the contrast of table 1 and table 2 we can clearly see that the curvelet features can achieve much better results than wavelet features on these two databases. In one hand, we find that using low frequency wavelet feature performs well relatively but still not exceeds the performance with the curvelet features of low frequency especially with fewer training samples. On the other hand, the performances received by curvelet features of detailed layers are all higher than wavelet features of high frequency.

Next we will consider the recognition performances if we combine the low frequency information with different high frequencies in decompositions. We have done all the experiemnts on these two datasets of facial images and the same conclusion is obtained, i. e. the best result is achieved by curvelet transform with its detailed information combination. We list the results in table 3 for JAFFE dataset and Cohn Kanade dataset. It can be seen that in all cases, the best perfromance is always achieved by curvelet transform.

TABLE I. PCA, LDA PERFORMANCE COMPARISONS

No. of training sample per expression	JAFFE 10	JAFFE 15	JAFFE 20	JAFFE 25	Cohn-Kanada 10	Cohn-Kanada 15	Cohn-Kanada 20	Cohn-Kanada 25
Curvelet LF+PCA+LDA	79.79%	86.10%	91.43%	94.57%	89.00%	94.67%	96.58%	98.78%
Curvelet Detail 1(4)+ PCA+LDA	73.64%	83.33%	89.00%	91.71%	76.61%	86.40%	96.00%	97.89%
Curvelet Detail 1(8)+ PCA+LDA	75.79%	84.48%	89.43%	94.00%	80.78%	89.07%	95.17%	99.11%
Curvelet Detail 2(4)+ PCA+LDA	66.93%	79.71%	88.86%	91.43%	81.67%	90.33%	96.58%	97.89%
Curvelet Detail 2(8)+ PCA+LDA	70.71%	81.62%	89.00%	93.43%	84.17%	93.60%	96.00%	99.67%
PCA	57.14%	69.42%	82.71%	88.86%	65.83%	76.93%	86.75%	96.33%
LDA	72.71%	82.76%	90.14%	93.42%	86.89%	90.91%	93.46%	96.17%

TABLE II. THE PERFORMANCE OF WAVELET FEATURES ON TWO DATABASES

No. of training sample per expression	JAFFE 10	JAFFE 15	JAFFE 20	JAFFE 25	Cohn-Kanada 10	Cohn-Kanada 15	Cohn-Kanada 20	Cohn-Kanada 25
Wavelet LF (2-level)	75.43%	84.95%	92.43%	94.86%	87.39%	94.40%	96.38%	99.11%
Wavelet compact HF(2-level)	50.57%	61.80%	65.71%	74.00%	71.17%	82.60%	88.00%	93.44%
Wavelet compact HF(3-level)	62.64%	74.38%	80.14%	87.71%	72.44%	81.87%	90.17%	94.11%
Wavelet diagonal HF(2-level)	41.75%	48.57%	53.71%	54.86%	67.78%	78.07%	86.03%	90.78%
Wavelet diagonal HF(3-level)	46.05%	52.76%	60.14%	63.43%	67.72%	76.06%	81.08%	84.66%

TABLE III. THE PERFORMANCES FOR CURVELET AND WAVELET WITH DIFFERENT COMBINATION OF FREQUENCIES.

No. of training sample per expression	JAFFE 10	JAFFE 15	JAFFE 20	JAFFE 25	Cohn-Kanada 10	Cohn-Kanada 15	Cohn-Kanada 20	Cohn-Kanada 25
Wavelet LF +compact LF (2-level)	76.07%	84.29%	88.43%	93.43%	88.11%	95.13%	97.33%	97.67%
Wavelet LF +compact LF (3-level)	75.86%	84.95%	87.43%	90.00%	87.94%	94.78%	96.50%	98.44%
Wavelet LF +diagonal LF (2-level)	74.21%	83.52%	88.71%	91.14%	85.83%	94.40%	97.33%	97.78%
Wavelet LF +diagonal LF (3-level)	74.21%	83.71%	88.71%	94.29%	86.72%	93.93%	96.25%	98.11%
Curvelet LF +Detail 1(4)	78.36%	86.48%	92.86%	96.57%	88.33%	96.07%	97.41%	99.11%
Curvelet LF +Detail 1(8)	77.07%	85.52%	92.57%	94.29%	90.67%	95.67%	96.58%	99.22%
Curvelet LF +Detail 2(4)	77.50%	87.14%	91.43%	94.57%	88.67%	95.47%	97.58%	98.67%
Curvelet LF +Detail 2(8)	77.29%	87.62%	90.43%	95.14%	91.28%	95.33%	97.33%	98.78%

V. CONCLUSIONS

Curvelet is an effective analytical method with multi-resolution, band pass and directions that are considered as three characteristics the "optimal" image representation should have from the perspective of biological point of view. It is recognized that the curvelet transform has better capability to represent image features than wavelet transform. Motivated by these observations, we proposed a new feature extraction technique using the curvelet transform and then use LDA method to recognize facial expressions. Extensive experiments have been conducted on two benchmark datasets and the experimental results show that the curvelet features can achieve much better results by using LDA compared to the wavelet features and pixel values.

There are two observations from the results of this paper. One is that the detailed information in the curvelet can present the images quite well and LDA can achieve much better result just based on such features. The other observation is that the curvelet has much better capability in characterize the features of images in low resolutions, which we did not present the results here due to space limitation. In the future, we will investigate how to use these curvelet features in other applications, like face recognition, object detection and surveillance.

Also the investigators in [17] used the wrapping curvelet to tackle the face recognition issue and we will explore such curvlet for facial expression recognition.

ACKNOWLEDGMENT

First we thank the three reviewers for their constructive comments in improving the quality of this paper. Also this paper is supported by a Science and Technology Planning project in Yunnan Province with grant number 2007F202M and a Chunhui Planning project from China Education Committ.

REFERENCES

[1] T. Kanade, J. Cohn, and Y. Tian, "Comprehensive Database for Facial Expression Analysis*," Proc. IEEE Int'l Conf. Face and Gesture Recognition (AFGR '00),*pp. 46-53, 2000.

[2] B. Vinay Kumar, "Face Expression Recognition and Analysis: The State of the Art", *Course Paper, Visual Interfaces to Computer*, May 2009.

[3] B. Fasel and J. Luttin, "Automatic Facial Expression Analysis: a survey," *Pattern Recognition,* vol. 36, no. 1, pp. 259-275, 2003.

[4] I. Kotsia, I. Buciu and I. Pitas, "An Analysis of Facial Expression Recognition under Partial Facial Image Occlusion," *Image and Vision Computing,*. 1052-1067, July 2008.

[5] H. K. Ekenel and R. Stiefelhagen, "Why is facial occlusion a challenging problem?" *International Conference on Biometrics, Sassari, Italy,* June 2009.

[6] Yan jingwen, Qu xiaobo, "Analysis and Application of Super-Wavelet", National Defence Industry Press, 2008.

[7] Zhen Lei, Shengcai Liao, Ran He, Matti Pietik¨ainen, Stan Z. Li, "Gabor Volume based Local Binary Pattern for Face Representation and Recognition," 978-1-4244-2154-1/08 _c 2008 IEEE.

[8] Jaffe dataset, `http://www.kasrl.org/jaffe.html`

[9] J. L. Starck, E. J. Candes, D. L. Donoho, "The curvelet Transform for Image Denoising," *IEEE Trans. on Image Processing*, Vol. 11, Issue 6, pp 670-684, 2002.

[10] Caifeng Shan , Shaogang Gong , Peter W . McOwan, "Facial expression recognition based on Local Binary Patterns: A comprehensive study," *Image and Vision Computing,* 27 (2009) 803–816.

[11] Xue Weimin, "Facial Expression Recognition Based on GaborFilter and SVM," *Chinese Journal of Electronics* , Vol.15, No. 4A. 2006.

[12] Praseeda Lekshmi. V. , Dr. M. Sasikumar, "Analysis of Facial Expression using Gabor and SVM," *International Journal of Recent Trends in Engineering,* Vol. 1, No. 2, May 2009.

[13] Candes E J, Demanet L, Donoho D L, et al. "Fast Discrete Curvelet Transforms[R]," California:California Institute of Technology, Applied and Computational Mathematics, 2006, pp.1-43.

[14] Candes E J, Donoho D. L., "Curvelet surprisingly effective non-adaptive representation for objects with edges," Curve and Sur-face Fitting: Saint-Malo, TN: Vanderbilt University Press,1999,105-120.

[15] G. C. Feng, P.C. Yuen, D.Q. Dai, "Human face recognition using PCA on wavelet subband," *SPIE Journal of Electronic Imaging,* 9 (2) (2000) 226–233.

[16] C. Garcia, G. Zikos, G.Tziritas, "Wavelet packet analysis for face recognition," *Image and Vision Computing*, 18 (4) (2000) 289–297.

[17] T. Mandal, A. Majumdar and J. Hu, "Face Recognition Via Curvelet Based feature Extraction", *International Conference on Image Analysis and Recognition*, pp. 806- 817, 2007.

[18] Xiaoou Tang and Xiaogang Wang, "Face Photo Recognition Using Sketch," 0-7803-7622-6/02/IEEE ICIP 2002.

[19] Z. Jiulong, Z. Zhiyu, H. Wei, L.Yanjun and W. Yinghui, "Face Recognition Based on Curvefaces," *Third International Conference on Natural Computation*, Vol.2, pp.627-631, 2007.

[20] M.S. Bartlett, G. Littlewort, I. Fasel, and R. Movellan, "Real Time Face Detection and Facial Expression Recognition: Development and Application to Human Computer Interaction," *Proc. CVPR Workshop on Computer Vision and Pattern Recognition for Human-Computer Interaction,*2003.

[21] V. Gomathi, Dr. K. Ramar, and A. Santhiyaku Jeevakumar, "Human Facial Expression Recognition using MANFIS Model," World Academy of Science, Engineering and Technology **,** 2009**.**

[22] B. Li, Y. Liu, "When eigenfaces are combined with wavelets, " *International Journal of Knowledge-Based Systems,* 15 (5/6) (2002) 343–347.

[23] Y.-L. Tian, L. Brown, A. Hampapur, S. Pankanti, A. Senior, and R. Bolle, "Real world real-time automatic recognition of facial expressions." *In Proceedings of IEEE Workshop on Performance Evaluation of Tracking and Surveillance*, Graz, Austria, 2003.

[24] M. Dailey, G. Cottrell, "PCA Gabor for expression recognition," Institution UCSD, Number CS-629, 1999.

[25] D. Q. Dai and H. Yan, "Wavelets and Face Recognition" in Face Recognition, K. Delac and M. Grgic ed., I-TECH Education and Publishing, Vienna, 2007.

[26] Fan CHEN, Kazunori KOTANI, "Facial Expression Recognition by SVM-based Two-stage Classifier on Gabor Features," MVA2007 *IAPR Conference on Machine Vision Applications,* May 16-18, 2007, Tokyo, JAPAN.

[27] Tanaya Mandal and Q. M. Jonathan Wu, "Face Recognition using Curvelet Based PCA," 978-1-4244-2175-6/08/©2008 IEEE.

[28] A. Majumdar and A. Bhattacharya, "Face Recognition by Multiresolution Curvelet Transform on Bit Quantized Facial Images", *IEEE International Conference on Computational Intelligence and Multimedia Applications*, pp. 209-213, 2007.