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Recognition of facial expressions using Gabor wavelets and learning vector quantization

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Abstract

Facial expression recognition has potential applications in different aspects of day-to-day life not yet realized due to absence of effective expression recognition techniques. This paper discusses the application of Gabor filter based feature extraction in combination with learning vector quantization (LVQ) for recognition of seven different facial expressions from still pictures of the human face. The results presented here are better in several aspects from earlier work in facial expression recognition. Firstly, it is observed that LVQ based feature classification technique proposed in this study performs better in recognizing fear expressions than multilayer perceptron (MLP) based classification technique used in earlier work. Secondly, this study indicates that the Japanese Female Facial Expression (JAFFE) database contains expressers that expressed expressions incorrectly and these incorrect images adversely affect the development of a reliable facial expression recognition system. By excluding the two expressers from the data set, an improvement in recognition rate from 87.51% to 90.22% has been achieved. The present study, therefore, proves the feasibility of computer vision based facial expression recognition for practical applications like surveillance and human computer interaction.

Keywords: Facial expression recognition; Gabor wavelets; Learning vector quantization; JAFFE; Principal component analysis

1. Introduction

Facial expressions provide an important behavioral measure for the study of emotions, cognitive processes and social interaction (Bartlett et al., 1999; Yuki et al., 2005) and thus automatic facial expression recognition systems can provide a less intrusive method to apprehend the emotion activity of a person of interest. With the availability of low cost imaging and computational devices, automatic facial recognition systems now have a potential to be useful in several day-to-day application environments like operator fatigue detection in industries, user mood detection in human computer interaction (HCI) and possibly in identifying suspicious persons in airports, railway stations and other places with higher threat of terrorism attacks.

Facial expression recognition is also a necessary step towards a computer facilitated human interaction system (Lyons et al., 1998) as facial expressions play a significant role in conveying human emotions. Any natural HCI system thus should take advantage of the human facial expressions.

There exists a debate in psychology and behavioral science literature regarding whether facial expressions are universal or not and also regarding whether facial expressions are "eruptions" (meaning facial expressions occur involuntarily) or "declarations" (meaning that they are voluntary) (Friudlund, 2006). Extreme positions taken by early theorists have gradually given way to recent interactionist perspectives integrating evidence for both universality and cultural specificity (Elfenbein and Ambady, 2003). Research has shown that facial expressions are correctly recognized by people universally at a rate greater than that allowed by chance alone and hence in this respect, facial expressions are universal. At the same time, research also shows that cultural exposure increases the

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chances of correct recognition of facial expressions indicating cultural dependence (Yuki et al., 2005; Elfenbein and Ambady, 2003, 2002).

Until recently, there were only two options for correct recognition of facial expressions: human observer based coding system (Elfenbein and Ambady, 2003) and electromyography (EMG) based systems (Cohn et al., 2002). Human observer based methods are time consuming to learn and use, and they are difficult to standardize, especially across laboratories and over time. The other approach, facial EMG, requires placement of sensors on the face, which may inhibit certain facial actions and which rules out its use for naturalistic observation. An emerging alternative is automated facial image analysis using computer vision (Cohn and Kanade, 2006). The research in computer vision based recognition of facial expressions has progressed for long irrespective of the psychological debate. The primary inspiration of such research efforts has been the human ability to recognize facial expressions by just looking at still or video images with a high rate of correct recognition. The potential benefits of computer recognition of facial expressions in security applications and HCI have been the motivations in most of the cases.

There are two different approaches commonly used in computer vision based facial expression recognition so far: recognition using 2D still images and recognition using image sequences. Approaches using image sequence often apply optical flow analysis to the image sequence and use pattern recognition tools to recognize optical flow patterns associated with particular facial expression (Cohn and Kanade, 2006; Amr Goneid and Rana el Kaliouby, 2002; Xiaoming Liu et al., 2002; Lien et al., 1999). This approach requires acquisition of multiple frames of images to recognize expressions and thus has limitations in real-time performance and robustness. Facial expression recognition using still images often use feature based methods (Lyons et al., 1998; Zhang et al., 1998; Chellappa et al., 1995; Marian Stewart Bartlett et al., 2003) for recognition and thus have fairly fast performance but the challenge in this approach is to develop a feature extraction method that works well regardless of variations in human subjects and environmental conditions.

Gabor filter banks are reasonable models of visual processing in primary visual cortex and are one of the most successful approaches for processing images of the human face (Fasel et al., 2002). Lyons et al. (1998) proposed a Gabor wavelet based facial expression coding system and show that their representation method has a high degree of correlation with the human semantic ratings. In Zhang et al. (1998), Gabor filter banks based facial expression coding for feature extraction and multilayer perceptron (MLP) based feature classification is reported to have performed better than geometric feature based facial expression recognition. In this paper, the feature extraction method proposed in Lyons et al. (1998) is adopted. Principal component analysis (PCA) is used for reducing the length of the feature vector.

Neural networks have been widely used for classification and recognition tasks. The use of neural networks in face recognition has addressed several problems: gender classification (Zehang Sun et al., 2002), face recognition (Lawrence et al., 1996) and classification of facial expressions (De Stefano et al., 1995). There are different architectures of neural networks each having their own strengths and drawbacks. Good performance of a given architecture in a particular problem does not ensure similar results in a different problem. In this paper, benefits of using a learning vector quantization (LVQ) are explored for recognition of facial expression rather than MLP as in Zhang et al. (1998). By using the same Japanese Female Facial Expression (JAFFE) database for training and testing, the performance of MLP reported in an earlier work (Zhang et al., 1998) is compared with that of LVQ for facial expression recognition.

The rest of the paper is organized as follows: image acquisition and preprocessing is discussed in Section 2 of this paper; Section 3 describes feature extraction and the PCA is discussed in Section 4. Section 5 describes the JAFFE database and Section 6 introduces classification approach adopted in this work. Section 7 presents the results and observations of this study and finally, the conclusion is presented in Section 8.

2. Image acquisition and preprocessing

A practical facial expression recognition system is shown in Fig. 1 below. The recognition process begins by first acquiring the image using an image acquisition device like a camera. The image acquired then needs to be preprocessed such that environmental and other variations in different images are minimized. Usually, the image preprocessing step comprises of operations like image scaling, image brightness and contrast adjustment and other image enhancement operations. In this study, an

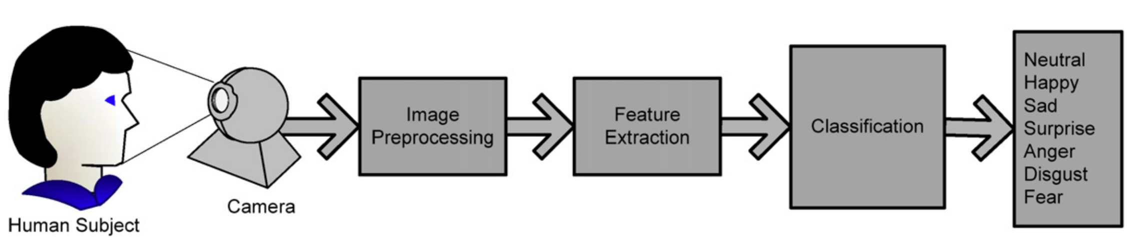

Fig. 1. Facial expression recognition system overview.

Fig. 2. Screen shot of the graphical user interface developed in Visual Basic 6.0.

existing image database of human facial expressions is used to train and test the performance of the classifier. The images in the database have already been preprocessed and thus there is no need to incorporate any image preprocessing operation in this study.

A graphical user interface application has been developed in Visual Basic to graphically select the fiducial points in the image. The geometric coordinates of the points for each image are then ported to Matlab for further processing. Fig. 2 shows the screen shot of the application.

3. Feature extraction

In order to recognize facial expressions from frontal images, a set of key parameters that best describe the particular set of facial expression needs to be extracted from the image such that the parameters can be used to discriminate between expressions. This set of parameters is called the feature vector of the image and the amount of information extracted from the image to the feature vector is the single most important aspect of successful feature extraction technique. If the feature vector of a face belonging to an expression matches with that of another face belonging to some other expression, no feature based classification technique can correctly classify both of the faces. This condition, called feature overlap, should never occur in an ideal feature extraction technique.

Good results can be obtained for facial emotion recognition on novel individuals using techniques applied in face recognition (Bartlett et al., 1999). Among several findings in image processing and compression research, feature extraction for face recognition and tracking using Gabor filter banks is reported to yield good results (Chellappa et al., 1995; Marian Stewart Bartlett et al., 2003; De Stefano et al., 1995; Dailey et al., 2002). Therefore, Gabor filter based feature extraction technique is a promising feature extraction technique for facial expression recognition. In Lyons et al. (1998), authors propose an approach for coding facial expressions with Gabor wavelets and (Zhang et al., 1998; Dailey et al., 2002) report a successful development of facial expression recognition system similar to the feature extraction approach proposed in Lyons et al. (1998). In order to compare the results of this study with that of Zhang et al. (1998), the feature extraction technique proposed in Lyons et al. (1998) has been adopted.

A 2-D Gabor function is a plane wave with wave-factor $\mathbf{k}$, restricted by a Gaussian envelope function with relative width σ:

$$\psi(k,x) = \frac{k^2}{\sigma^2}\exp\left(-\frac{k^2x^2}{2\sigma^2}\right)\left[\exp(ik.x) - \exp\left(-\frac{\sigma^2}{2}\right)\right]. \tag{1}$$

The value of σ is set to π for the image of resolution 256×256. Like in Lyons et al. (1998) and Zhang et al. (1998), a discrete set of Gabor kernels is used that comprises of 3 spatial frequencies (with wave-number $k = \pi/4$, $\pi/8$, $\pi/16$) and 6 distinct orientations from 0° to 180°, differing in 30° steps that makes a filter bank of altogether 18 different Gabor filters. Fig. 3 shows the 18 different Gabor filter kernels obtained as described above.

These Gabor filters are applied to each of the images and filter responses are obtained only at predefined fiducial points. In order to compare the performance of LVQ in this paper with that of MLP, same 34 fiducial points are used to obtain the Gabor filter bank response as suggested by Zhang et al. (1998). This results in a feature vector of length 612 (34 fiducial points, 18 filter responses per point) that represents the facial expressions in the input image. Fig. 4 shows the typical response of the Gabor filters to an input image. It can be observed from the figure how the changes in orientation and wave-factor in the Gabor filter affect the response of the image.

Fig. 5 shows the location of the 34 fiducial locations in the human face from where Gabor filter responses are sampled.

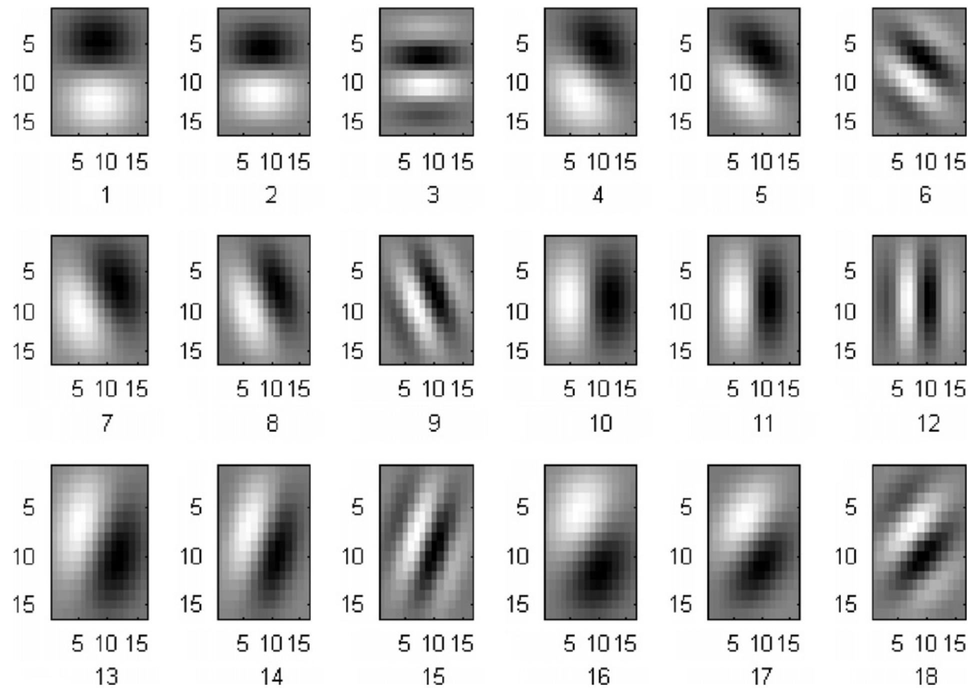

Fig. 3. 16×16 Gabor filter kernels used to obtain the feature vector.

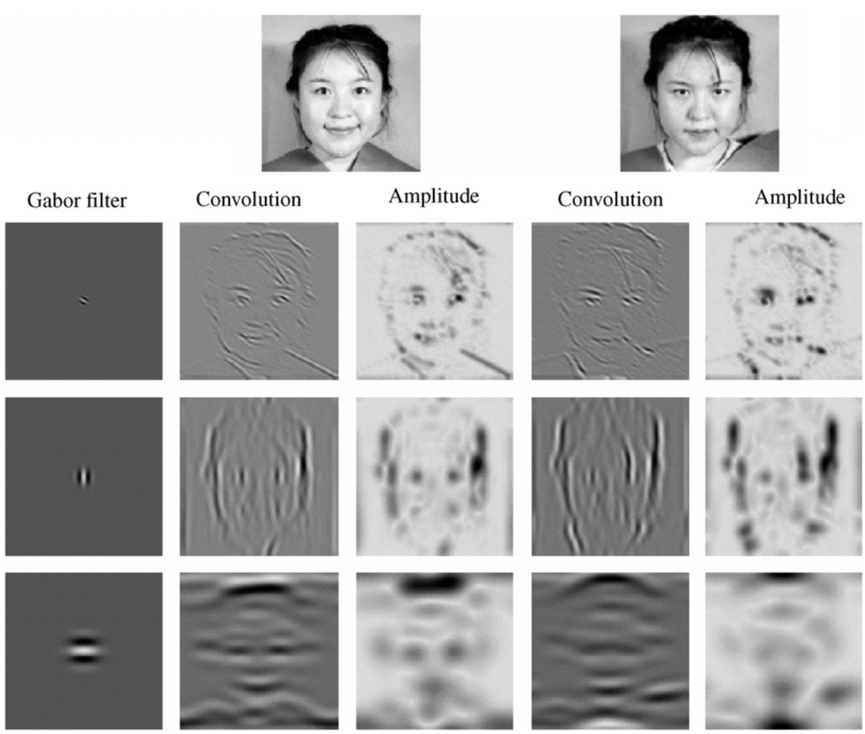

Fig. 4. Gabor filter responses for two sample images (Source: Zhang et al., 1998).

4. Principal component analysis

PCA is a technique used to lower the dimensionality of a feature space that takes a set of data points and constructs a lower dimensional linear subspace that best describes the variation of these data points from their mean. PCA is a linear transformation commonly used to simplify a data set by reducing multidimensional data sets to lower dimensions. By using PCA, dimensionality reduction in a data set can be achieved while retaining those characteristics of the data set that contribute most to its variance, keeping lower-order principal components and ignoring higher-order ones. PCA has the distinction of being the optimal linear transformation keeping the subspace that has largest

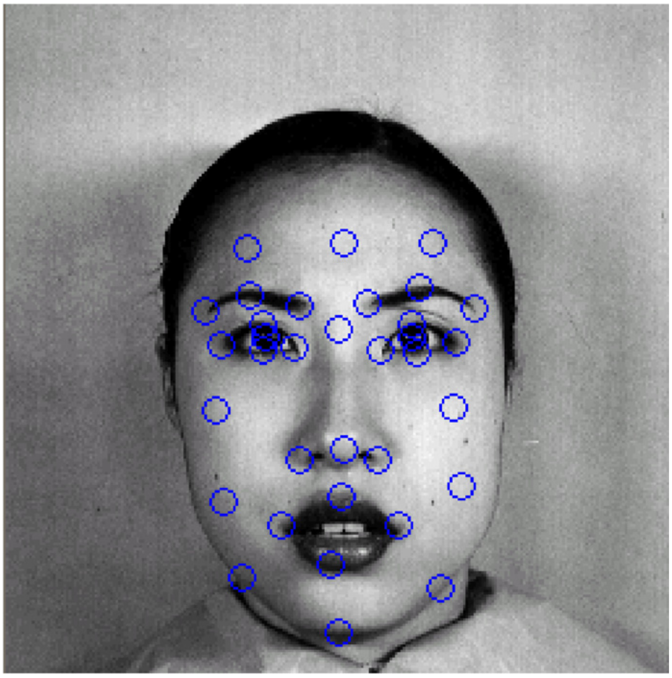

Fig. 5. Locations of 34 fiducial points used in this study.

variance. Unlike other linear transforms, PCA does not have a fixed set of basis vectors and its basis vectors depend on the data set. In this study, matlab inbuilt function prepca has been used to reduce the dimensionality of the feature vector from 612 to a desired length. In this study, the length of feature vector is gradually increased from 10 until the increase in the length of the feature vector does not result in significant improvement in the recognition rate.

5. JAFFE database

The JAFFE database (Lyons et al., 1998; Zhang et al., 1998) used in this study contains 213 images of female facial expressions. Each image has a resolution of 256×256 pixels. The number of images corresponding to each of the 7 categories of expression (neutral, happiness, sadness, surprise, anger, disgust and fear) is almost the same. Two of the expressers are shown in Fig. 6.

The images in the database are grayscale images in the tiff file format. The expression expressed in each image along with a semantic rating is provided in the database that makes the database suitable for facial expression research. The heads in the images are mostly in frontal pose. Original images have already been rescaled and cropped such that the eyes are roughly at the same position with a distance of 60 pixels in the final images. The arrangement used to obtain the images in the database consisted of a table-mounted camera enclosed in a box. The user-facing side of the box had a semi-reflective plastic sheet. Each subject took a picture while looking at the reflective sheet (towards the camera). Each subject's hair was tied away from the face to expose all expressive zones of the face. Tungsten lights were positioned to create an even illumination on the face. The images were printed in monochrome and digitized using a flatbed scanner. The actual names of the subjects are not revealed but they are referred with their initials: KA, KL, KM, KR, MK, NA, NM, TM, UY and YM.

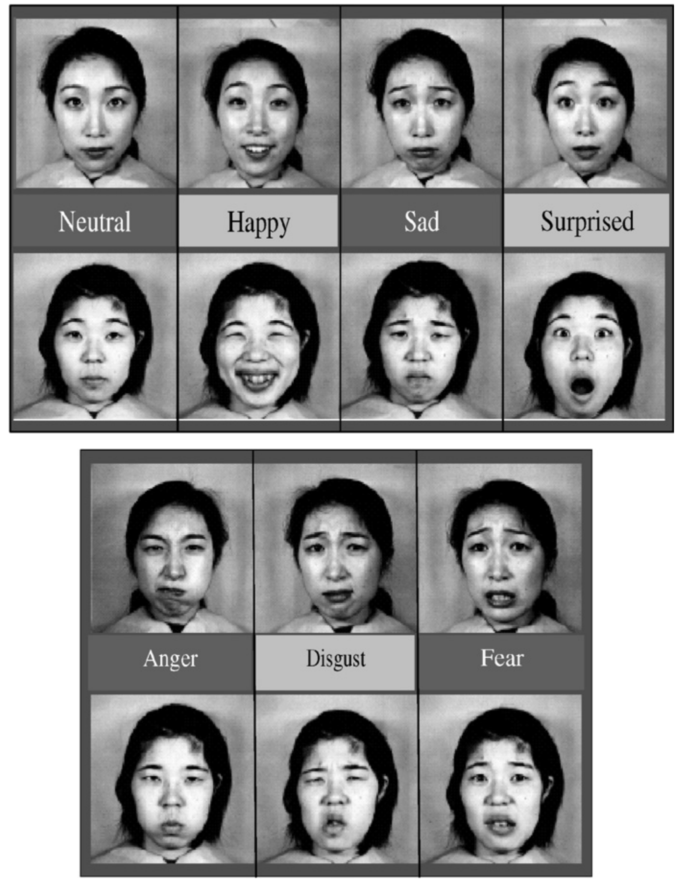

Fig. 6. Sample expressions of two expressers from the JAFFE database.

Each image in the database was rated by 91 experimental subjects for degree of each of the six basic expressions present in the image. The semantic rating of the images showed that the error for the fear expression was higher than that for any other expression but there exist a number of cases even for other expressions in which the expression getting highest semantic rating is different from the expression label of the image.

6. Learning vector quantization

LVQ, developed by Kohonen, is one of the most frequently used unsupervised clustering algorithms and is based on the winner-takes-all philosophy. There exist several versions of LVQ (Kohonen, 2001) and LVQ-I has been used in this study.

LVQ-I has two layers: competitive and output. The neurons in the competitive layer are also called sub-classes. Each sub-class has a weight vector similar to the input vector. When an input vector is applied to an LVQ network, the best match is searched in the competitive layer and the best match is called the winning neuron. When a particular neuron in the competitive layer wins, the particular output belonging to the class of the neuron is set high. Multiple neurons in the competitive layer may correspond to the same class in the output layer but a neuron in the competitive layer is associated only with a particular class. It is for this reason that the neurons in the competitive layer are called sub-classes (Fig. 7).

The learning method commonly used with LVQ is the competitive learning rule in which for each training pattern, the competitive layer neuron that is the closest to the input is determined and the corresponding output neuron is called the winner neuron. The weights of the connections to this neuron are then adapted using the following equation:

$$w_i^1(n) = \begin{cases} w_i^1(n-1) + \alpha(p - w_i^1(n-1)) & \text{if classification is correct} \\ w_i^1(n-1) - \alpha(p - w_i^1(n-1)) & \text{otherwise} \end{cases} \tag{2}$$

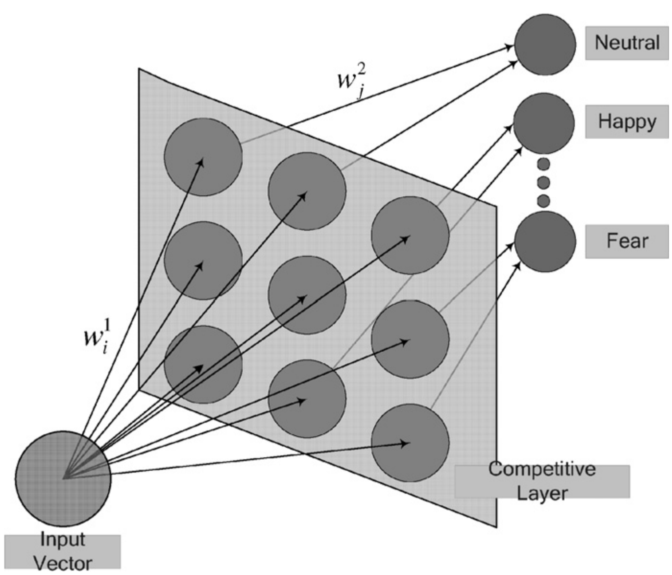

Fig. 7. Structure of a learning vector quantization network.

In Eq. (2), w_i is the input layer weight, p is the input vector and α is the learning rate. The direction of the weight adaptation when using Eq. (2) depends on whether the class of the training pattern and the class assigned to the reference vector are same or not. If they are same, the reference vector is moved closer to the training pattern; otherwise it is moved farther away. This movement of the reference vector is controlled by the learning rate. It states as a fraction of the distance to the training pattern how far the reference vector is moved. Usually the learning rate is decreased in the course of time, so that initial changes are larger than changes made in later epochs of the training process.

7. Results and discussion

Initially, learning rate of the network is varied to find out the best learning rate for the classification task. It is found that the learning rate of 0.08 works best with the network. The length of the feature vector is then varied to achieve a satisfactory network performance. PCA technique is used to arrange the feature vector in descending order of variance and is truncated at desired length to find out if that length for feature vector is sufficient for correct recognition of facial expressions. All 213 images in the database are used for this task of experimentation with the length of the feature vector and the learning rate parameter is set to 0.08 at all times. To describe the performance of a given network, 100 LVQ networks are created and trained with feature vector of certain length and the mean and standard deviation of the recognition rate for the 100 networks is reported as the comparison parameter. For each network, the training is stopped after 300 iterations. In this study, the feature vector length is varied from 10 to 100 in steps of 10. Table 1 shows the result of the experimentation with variation in length of the feature vector.

Table 1 shows that the performance is best when the length of the vector is set to 90. Further increase in the length of the feature vector does not improve the performance but degrades the speed of the LVQ network,

Table 1
Result of varying the length of the feature vector

Feature vector length	Mean training error (N images out of 163)		Mean testing error (N images out of 50)		Total mean error (out of 213)	Overall accuracy (%)
	(N)	(%)	(N)	(%)		
10	35.6±4.16	21.8±2.55	24.5±3.4	49.00±6.8	60.10	71.78
20	25.2±3.12	15.4±1.91	20.7±3.6	41.40±7.2	45.90	78.45
30	18.9±[2.48	11.6±1.52	18.5±3.4	37.00±6.8	37.40	82.44
40	17.0±2.44	10.4±1.50	17.4±3.5	34.80±7.0	34.40	83.85
50	15.2±2.43	9.3±1.49	17.2±3.3	34.40±6.6	32.40	84.79
60	13.4±2.07	8.2±1.27	16.8±3.5	33.60±7.0	30.20	85.82
70	12.4±1.94	7.6±1.19	16.6±3.3	33.20±6.6	29.00	86.38
80	11.4±2.01	7.0±1.23	17.0±3.8	34.00±7.6	28.40	86.67
90	10.4±1.86	6.4±1.14	16.2±3.7	32.40±7.4	26.60	87.51
100	10.0±2.23	6.1±1.37	16.6±3.5	33.20±7.0	26.60	87.51

Table 2
Result of varying the number of sub-classes per expression

Sub-class size	Mean training error (N images out of 163)		Mean testing error (N images out of 50)		Total mean error (out of 213)	Overall accuracy (%)
	(N)	(%)	(N)	(%)		
35	24.0±3.05	14.7±1.9	21.2±3.65	42.4±7.3	45.20	78.78
42	19.5±2.85	11.9±1.8	19.5±3.82	39.0±7.6	39.00	81.69
49	16.0±2.50	9.8±1.5	18.6±3.40	37.2±6.8	34.60	83.76
56	13.0±2.20	7.9±1.3	17.8±3.99	35.6±8.0	30.80	85.54
63	12.0±2.48	7.3±1.5	17.3±3.95	34.6±7.9	29.30	86.24
70	11.2±2.01	6.8±1.2	16.6±3.07	33.2±6.1	27.80	86.95
77	10.4±1.86	6.3±1.1	16.2±3.68	32.4±7.3	26.60	87.51

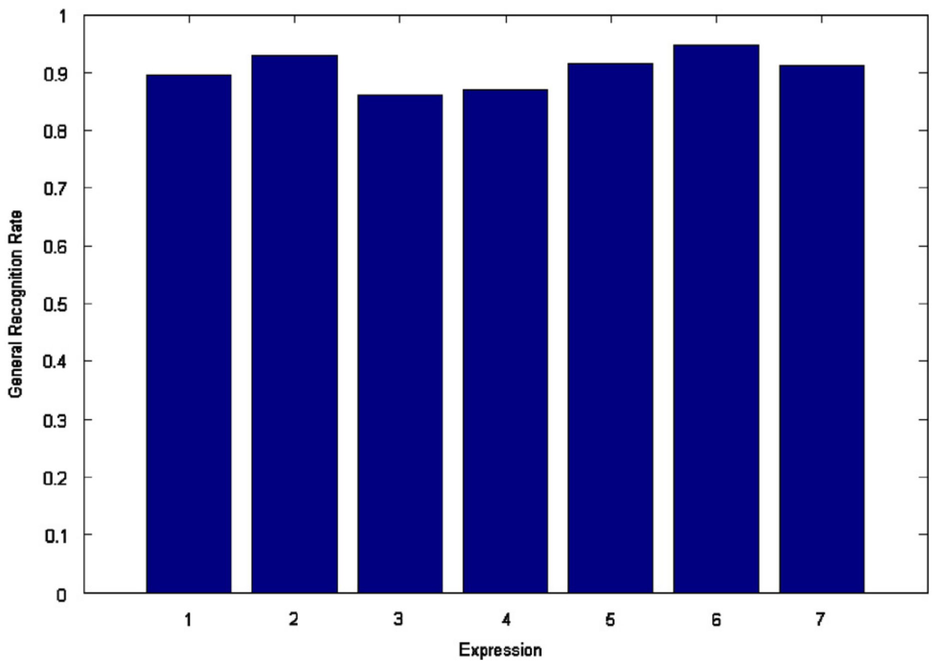

Fig. 8. Recognition rate for different expressions.

as more computation is required. In this experiment, number of sub-classes was set to 77. After finding out the proper length of the feature vector, the number of sub-classes per expression is varied to find the optimal size for the competitive layer. In this study, the length of the feature vector was set to 90 and the sub-class size was varied from 35 to 77 in steps of 7. Equal number of sub-classes is used for each of the expressions in this experiment and Table 2 summarizes the result.

It can be observed from Table 2 that the increase in the number of sub-classes above 8 per expression (i.e. sub-class size larger than 56) does not significantly improve the performance of the network. This is because once there are enough weights to cover the cluster belonging to the particular expression in the problem space; the increase in number of sub-classes does not have a significant effect. Moreover, when the sub-class size is large for a given problem, the LVQ network over-fits the training data and lacks the desired generalization capability. As the network performance is found to be good with 11 sub-classes per expression, sub-class size of 77 (11 sub-classes for each 7 expressions) is used in the competitive layer of the network without increasing the size any further.

There are two important observations to be made here. Firstly, earlier work that used the same database and the same feature extraction technique but a different learning algorithm reported that the human evaluators as well as their network had problems in correctly identifying the fear expression. Above experiments show that for a particular architecture, the generalization obtained is as high as 87.51% and is comparable to the generalization of the earlier work obtained after removing the fear expression. In order to analyze the performance of the classifier in recognizing individual expressions, a testing set of 70 images is produced from the JAFFE database. The test set consists of 7 images for each of the 10 expresser, one image per expression. The other images are then used for training. Fig. 8 shows the generalized recognition rate for 7 different

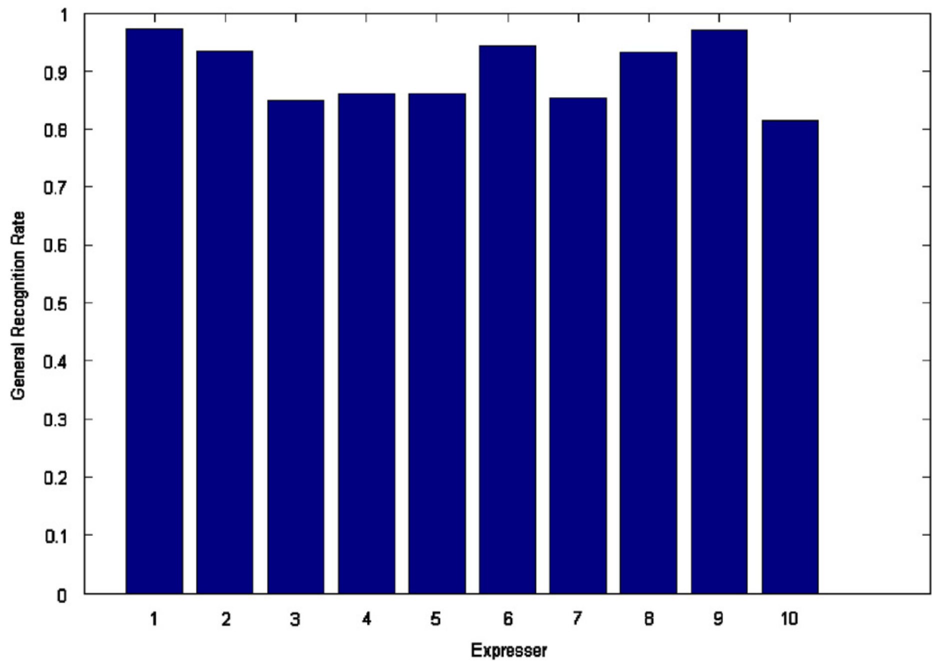

Fig. 9. Recognition rates for different expressers.

Table 3
Result of removing expressers UY and NA from the dataset

Mean training error (*N* images out of 131)		Mean testing error (*N* images out of 40)		Total mean error (out of 171)	Overall accuracy (%)
(*N*)	(%)	(*N*)	(%)		
4.37 ± 1.45	3.34 ± 1.11	12.35 ± 3.09	30.87 ± 7.7	16.72	90.22

expressions. Unlike reported by earlier work, the recognition rate is almost uniform for all expressions including fear.

Secondly, the network does not acquire a 100% correct classification even for the training data. An effort was made to analyze the recognition rate for individual images, which showed that some of the images in the data set could not be properly classified even when the images were used for training. This sort of response indicates that the images have a problem in either the expressers expressing the expression or in the labeling of the images.

A learning algorithm suffers a lot when there are errors in the training data as the network may inherit the errors. The presence of erratic expressions explains why an accuracy of 100% was not achieved even for the images in the training sample. Fig. 9 presents the recognition rate of LVQ network for 10 expressers.

It is observed that the images in the range 134–154 and 199–219 are highly erratic. The images 134–154 all belong to the expresser UY in the data set and the images 199–219 all belong to expresser NA. The problem apparently is in the expressers expressing the expressions. Experiments then carried out by removing these two expressers from the data set led to increase in recognition rate by almost 3%. For this experiment, the length of the feature vector was set to 90 and the sub-class size was set to 77. The results of the experiment are tabulated in Table 3. The reduced data set still includes fear expression images except those that belonged to the two expressers.

8. Conclusions and future work

The present study successfully used LVQ algorithm for facial expression recognition and Gabor filter banks as the feature extraction tool. The result of the study is better than that reported by earlier work using MLP instead of the LVQ. Earlier work reported having problem in classifying fear expressions but the approach presented here is equally good in discriminating fear expressions. Generalized accuracy of 87.51% is achieved for the entire data set. By excluding 42 images belonging to two erratic expressers from the data set, an improvement in recognition rate by 3% is achieved with generalized recognition rate of 90.22%. The result is encouraging enough to explore real-life applications of facial expression recognition in fields like surveillance and user mood evaluation.

Further work involves evaluating the performance of the trained network on other standard facial expression database.

Modification of the present approach is being studied to detect mixed-emotions (for example, happiness and surprise, fear and disgust) that may occur in the human face.

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