Vector Quantization Based Face Recognition Using Integrated Adaptive Fuzzy Clustering

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Abstract. A face recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame. In this paper, an improved codebook design method is proposed for Vector Quantization (VQ)-based face recognition which improves recognition accuracy. A codebook is created by combining a systematically organized codebook based on the classification of code patterns and another codebook created by Integrated Adaptive Fuzzy Clustering (IAFC) method. IAFC is a fuzzy neural network which incorporates a fuzzy learning rule into a neural network. The performance of proposed algorithm is demonstrated by using publicly available AT&T database and Yale database. The evaluation has been done using two methodologies; first with no rejection criteria, and then with rejection criteria By applying the rejection criteria an equal error rate of 3.5 % is obtained for AT & T database and 6 % is obtained for Yale database Experimental results also show the face recognition using the proposed codebook with no rejection criteria is more efficient yielding a rate of 99.25% for AT & T and 98.18% for Yale which is higher than most of the existing methods.

Keywords: Face Recognition, Vector Quantization, Codebook, Integrated Adaptive Fuzzy Clustering, Self Organization Map.

1 Introduction

In most situations face recognition is an effortless task for humans. Machine Recognition of faces from still and video images is emerging as an active research area spanning several disciplines such as image processing, pattern recognition, computer vision, neural networks etc [1]. Face recognition technology has numerous commercial and law enforcement applications [1]. Applications range from static matching of controlled format photographs such as passports, credit cards, photo IDs, driver‘s licenses to real time matching of surveillance video images [1].

A lot of algorithms have been proposed for solving face recognition problem [2]. Among these Principal Component Analysis (PCA) is the most common one. PCA [3] is used to represent a face in terms of an optimal coordinate system which contains the most significant eigenfaces where the mean square error is minimal. Fisherfaces

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[4] which use Linear Discriminant Analysis (LDA); Bayesian methods[5], which use a probabilistic distance metric; and SVM methods [6], which use a support vector machine as the classifier, are also present. Being able to offer potentially greater generalization through learning, neural networks have also been applied to face recognition [7]. Feature-based approach [8] uses the relationship between facial features, such as the locations of eye, mouth and nose. Local Feature Analysis (LFA) [9], local autocorrelations and multiscale integration technique [10], etc are some of the methods.

Kotani et al. [11] have proposed a very simple yet highly reliable VQ-based face recognition method called VQ histogram method by using a systematically organized codebook for 4x4 blocks with 33 codevectors. Chen et al [12] proposed another face recognition system based on an optimized codebook which consists of a systematically organized codebook and a codebook created by Kohonen‘s Self Organizing Maps (SOM) [16].

VQ algorithm [13] is well known in the field of image compression. A codebook is very important since it directly affects the quality of VQ processing. In [12] an optimized codebook is created based on classification of code patterns and SOM. The Kohonen self-organizing feature map has to assume the number of clusters a priori and to initialize the cluster centroids. SOM guarantee convergence of weights by ensuring decrease in learning rates with time. Such learning rates, however, do not consider the similarity of the input pattern to the prototype of the corresponding cluster [17].

In this paper an improved codebook design method for VQ-based face recognition is proposed. At first a systematically organized codebook is created based on the distribution of code patterns [12], and then another codebook with the same size is created using Integrated Adaptive Fuzzy Clustering Method (IAFC) [17]. IAFC addresses the problems associated with SOM. In IAFC a fuzzy membership value is incorporated in the learning rule. This fuzzy membership value of the input pattern provides additional information for correct categorization of the input patterns. Moreover IAFC does not assume the number of clusters in the data set a priori, but updates it during processing of data [17].

The two codebooks are combined to form a single codebook which consists of 2x2 codevectors. By applying VQ the dimensionality of the faces are reduced. The histograms of the training images are created from the codevectors. This is considered as the personal identification information. It can represent the features of the facial images more adequately. The system was tested using publicly available AT & T database and Yale database. A recognition rate of 99.25% and 98.18% are obtained for AT & T and Yale respectively without rejection. By applying the rejection criteria an equal error rate of 3.5 % is obtained for AT & T database and 6 % is obtained for Yale database.

The rest of the paper is organized as follows: Proposed face recognition system based on systematically organized codebook and IAFC is explained in section 2. Proposed Adaptive Codebook design is discussed in section 3. Experimental results are presented and discussed in section 4. Conclusions are given in section 5.

2 Design of the Proposed Face Recognition System

The proposed method starts with the pre-processing step. Preprocessing is explained in detail in section 2.1.During pre-processing each face image in the training set is processed to get the intensity variation vectors. Vector Quantization (VQ) is then applied to these vectors by using the proposed codebook which is a combination of two codebooks. The first codebook is developed by code classification [12]. The second codebook is created using IAFC [17]. During VQ the most similar codevector to each input block is selected.

After performing VQ, matched frequencies for each codevector are counted and histogram is saved in the database as Personal Identification Information. This histogram becomes the feature vector of the human face. Thus histogram is a very effective personal feature for discriminating between persons.

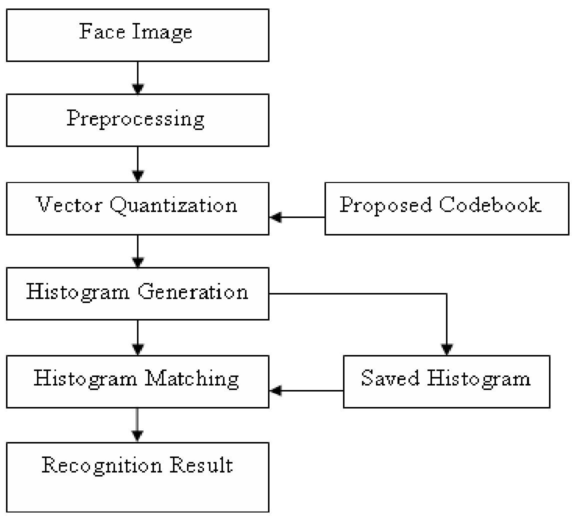

Fig. 1. Proposed Face Recognition System without rejection

In the recognition procedure, the histogram made from an input test image is compared with registered individual histograms and the best match is output as the recognition result. Manhattan distance between the histograms is used as the matching measure. Figure 1 shows the block diagram of the proposed method without rejection

For practical applications of face recognition, not a simple recognition rate but a False Accept Rate (FAR) and a False Reject Rate (FRR) are more important [11]. To calculate FAR and FRR rejection rate is also needed. The simplest way to add rejection ability is to set a threshold on the minimum Manhattan distance, which is denoted by *Th* and to reject a face if *Th,* exceeds this threshold. Based on this rejection criteria the image is either recognized (classified as a known person) or rejected (classified as unknown person).Figure 2 shows the block diagram of the proposed method with rejection.

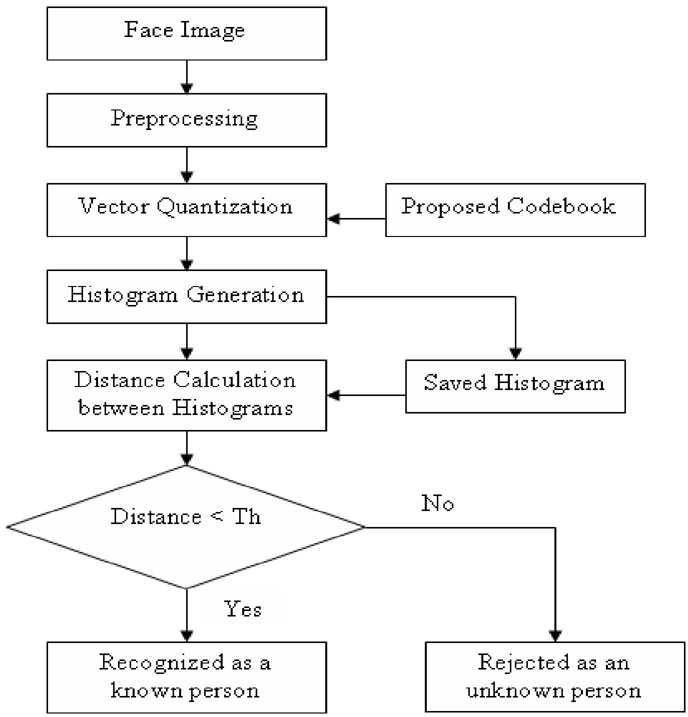

Fig. 2. Proposed Face Recognition System with rejection

Codebook which consists of typical feature patterns for representing the features of the face image is important. The proposed codebook design is explained in section 3.2

2.1 Preprocessing

During preprocessing initially a low pass filtering is carried out using a simple 2D mean filter [11]. A low pass filtering is effective for eliminating the noise component. By applying the filter, detailed facial features degrading recognition performance such as wrinkles and local hairstyle, are excluded. Only the important personal features, such as the rough shape of facial parts can be extracted.

The image is then divided into 2x2 overlapping blocks. Minimum intensity of the individual block is subtracted from each pixel in the block. Minimum intensity subtraction effectively excludes dc and vary low frequency component, such as shade variations due to small variations in lighting conditions and retains only the relevant information for distinguishing images. The preprocessing steps are explained in figure 3.

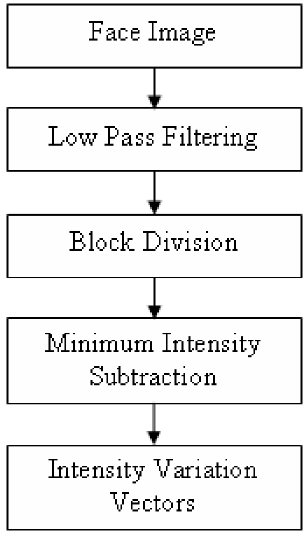

Fig. 3. Preprocessing Steps

3 The Proposed Adaptive Codebook Design

The proposed codebook for VQ is obtained from two codebooks. One codebook with size N is obtained by code classification [12] which is explained in section 3.1. This codebook is created by the variation in the intensity of the code patterns. It does not consider the intensity variations of the face images. So it cannot represent the facial features efficiently. So a second codebook is needed from the facial images to represent the facial features more efficiently.

In [12] a second codebook is created using Kohonen‘s SOM [16]. The self-organizing feature map self-organizes its weights by incremental adjustments in proportion to the difference between the current weight and the input pattern. In real applications, it is often difficult to assume the number of clusters present in many real data sets. And, different initial conditions result in different results. This neural network also requires considerable time to train [17]. In the proposed method the second codebook is created using IAFC [17] of the same size N. In IAFC a fuzzy membership value is incorporated in the learning rule. This fuzzy membership value helps in the correct categorization of the input patterns. Also IAFC does not assume the number of clusters in the data set a priori, but updates it during processing of data [17].

Thus a codebook of size 2N is obtained. To reduce the size of the codebook from 2N to N, the face images in the training set is preprocessed to get the intensity variation vectors. Then VQ is applied to these intensity variation vectors, matched frequencies of each codevector are counted and histogram of each face image is generated. Then the average histogram of all images is calculated. Next, the frequencies of individual codevectors are sorted. From this sorted 2N codevectors, only the high frequency N codevectors are selected. Thus, the final codebook consisting of 2x2 codevectors is generated.

3.1 Codebook Generated by Code Classification

Nakayama et al [14] have developed complete classification method for 2x2 codebook design in image compression. Figure 3 shows all categories for the 2x2 image block patterns without considering the location of pixels. In a 2x2 block, pixel intensities are marked by alphabet ‘a‘, ‘b‘, ‘c‘, ‘d‘, and a > b > c > d is prescribed. In ref. [14], it was found that the number of typical patterns for all 2x2 image block is only 11. The number of varieties in pixel arrangement of each 2x2 typical pattern is also shown in figure 4. That means the total number of image patterns for 2x2 pixel blocks is theoretically only 75.By the similar consideration, Chen et al [15] classified and analyzed the code patterns in the face images. They found that in all filter size, the number of code patterns belong to categories 7, 10, and 11 are very few. It means such code patterns are almost not used in face images. Based on this result, a new codebook for 2x2 code patterns is created, and the rules of codebook creation are as follows.

- Change the intensity difference among the blocks to from 1 to 10.
- Create very small intensity variation codes. The total number of patterns is 16
- Create code patterns of category no: 2,3,4,5,6,8 and 9
- Add one code pattern having no intensity variation

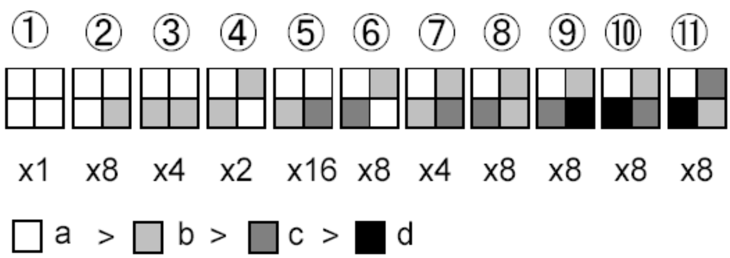

Fig. 4. Categories of 2x2 code patterns

3.2 Codebook Design Using IAFC

The lAFC model is a fuzzy neural network which incorporates a fuzzy learning rule into a neural network [17]. The learning rule, developed in IAFC, incorporates a fuzzy membership value (μ_i), an intracluster membership value (π), and a function of the number of iterations (f (l)) into a Kohonen-type learning rule. The number of clusters in IAFC is updated dynamically. An intracluster membership value (π) is decided by the distance between the input pattern and the centroid of the chosen cluster. The combination of the π-function and a function of the number of iterations guarantee weights to converge. The lAFC model incorporates a similarity measure that includes a fuzzy membership value into the Euclidean distance. The similarity measure considers not only the distance between the input data point and the centroid of a winning cluster but also the relative location of the input point to the existing cluster centroids as the degree of similarity. Thus, it gives more flexibility to the shape of clusters formed [17].

IAFC consists of three major procedures: deciding a winning cluster, performing the vigilance test, and updating the centroid of a winning cluster. The input pattern X is normalized prior to presentation to the fuzzy neural network and this normalized input pattern is fed to the fuzzy neural network in parallel to the input pattern. A dot-product operation used to find the winner is shown below

$$I \bullet b_i = \frac{X \bullet v_i}{\|X\| \bullet \|v_i\|} \tag{1}$$

Where *bi* is the normalized weights from the input neurons to the ith output cluster, and v_i is the i^{th} cluster centroid. The output neuron that receives the largest value for the equation (1) wins the competition. In this process, the winner is decided by the angle between the input pattern and the centroids of clusters. This can cause misclassifications because a cluster of which the direction of the centroid vector has the smallest angle with the input vector wins the competition even though its centroid is located farther from the input pattern than other cluster centroids. In such a case, Euclidean distance can be used as a better similarity measure to determine a winner. However, cluster centroids cannot approach appropriate locations during the early stage of learning, thus causing poor performance of clustering algorithms. To prevent both problems, the IAFC algorithm uses a combined similarity measure to decide a winner.

After deciding a winner by the dot product, the IAFC algorithm compares the fuzzy membership value, μ_i of the input pattern in the winning cluster with the parameter σ that user can decide as a threshold of the fuzzy membership value. If the fuzzy membership value is less than the value of the parameter σ, the angle between the input pattern and the cluster centroid is the dominant similarity measure to decide a winner. On the other hand, if the parameter σ is high, the Euclidean distance between the input pattern and the cluster centroid is the dominant similarity measure to decide a winner. After selecting a winning cluster, IAFC performs the vigilance test according to the criterion:

$$e^{-\gamma\mu_i}\|X - v_i\| <= \tau \tag{2}$$

Where γ is a multiplicative factor that controls the shape of clusters, X is the input pattern, v_i is the centroid of the i^{th} winning cluster, τ is the vigilance parameter and the value of γ is normally chosen to be 1[17]. The fuzzy membership value μ_i, is calculated as follows:

$$\mu_i = \frac{\left(\dfrac{1}{\|X - v_i\|^2}\right)^{1/m-1}}{\sum_{j=1}^{n}\left(\dfrac{1}{\|X - v_j\|^2}\right)^{1/m-1}} \tag{3}$$

Where m is a weight exponent which is experimentally set to 2 [17] and n is the number of clusters. If a winning cluster satisfies the vigilance criterion, the centroid of a winning cluster is updated as follows:

$$v_i^{new} = v_i^{old} + \lambda_{fuzzy}\left(X - v_i^{old}\right) \tag{4}$$

Where λ_{fuzzy} is [f(l). π(X; $v_i^{(old)}$; τ). μ_i^2].f(l) is a function of number of iterations, l being the number of iterations, and π decides the intra-cluster membership value of the input pattern X in the ith cluster as:

$$\pi(X; v_i^{(old)}; \tau) = \begin{cases} 1 - 2\left(\dfrac{\left\| X - v_i^{old} \right\|}{\tau}\right)^2, 0 \le \left\| X - v_i^{old} \right\| \le \tau/2 \\ 2\left(1 - \dfrac{\left\| X - v_i^{old} \right\|}{\tau}\right)^2, \tau/2 \le \left\| X - v_i^{old} \right\| \le \tau \\ 0, \left\| X - v_i^{old} \right\| \ge \tau \end{cases} \tag{5}$$

And

$$f(l) = \frac{1}{k(l-1)+1} \tag{6}$$

Where k is a constant

IAFC algorithm for the codebook design can be summarized by the following steps:

1. Initialize parameters τ and σ.
2. Transform the facial images in dataset to intensity variation vectors, and combine all vectors together into one training set.
3. Initialize the weight vectors with the intensity variation vectors.
4. Select a new input pattern from the training set.
5. Decide a winning cluster (best matching codevector) using the combined similarity measure.

   5(a) Calculate the dot product between the normalized input pattern and the normalized weight vector using equation (1).
   5(b) Calculate the Euclidean distance between the input pattern and the weight vector.

6. Calculate the fuzzy membership value, μ_i of the input pattern in the winning cluster using equation (3).

6(a) If $\mu_i < \sigma$,
the winner neuron is selected from 5(a)
else
the winner neuron is selected from 5(b)

7. Perform the vigilance test using equation (2). If the criterion is satisfied then update the weights using equation (4).
8. If all the input patterns are processed go to step 9 else go to step 4.
9. Stop.

4 Experimental Results and Discussions

Publicly available AT & T database [18] and Yale database [19] are used for recognition experiments. The AT & T database contains 400 images in pgm format of 40 persons. There are 10 different images of each of 40 distinct subjects. The images were taken at different times, varying the lighting, facial expressions (open / closed eyes, smiling / not smiling) and facial details (glasses / no glasses) [18]. The Yale Face Database contains 165 grayscale images in GIF format of 15 individuals. There are 11 images per subject, one per different facial expression or configuration: center-light, with glasses, happy, left-light, without glasses, normal, right-light, sad, sleepy, surprised, and wink [19]. Initially, the system has been tested with no rejection criteria. Then, a rejection criterion has been imposed into the system. The results without rejection and with rejection are explained in section 4.1 and 4.2 respectively.

4.1 Experiments with No Rejection Criteria

Five images were selected from each person's 10 images (in the case of AT & T) and from 11 images (in the case of Yale) for training purpose. The remaining images are used for testing. So 200 images from AT & T are used for training and the remaining 200 is used for testing. But in the case of Yale 75 images are used for training and 90 images are used for testing.

It is necessary to choose a suitable size for the codebook. As the codebook size is large, number of codevectors increases, the resolution of histogram may become so sensitive that noise corrupted codevectors may distort the histogram. On the contrary, if the number of codevectors is small, the histogram cannot sufficiently discriminate between faces. Recognition rate was observed for the codebook sizes 50, 60, 70, 80, 90, 100 and 110. It is clear from the figures 5 and 6 that the best performance is obtained with a codebook of size 80 for AT & T and with sizes 70 and 80 for Yale. With that size a recognition rate of 99.25% is obtained for AT & T and 98.18 % is obtained for Yale.

Figures 5 and 6 also show a comparison between the proposed approach and the existing method with SOM [16]. It is clear from the figures that in all the cases the proposed method yields a better recognition result than the existing method. It can be said that the proposed codebook is more efficient in representing the facial features than the existing method using systematically organized codebook and SOM [12].

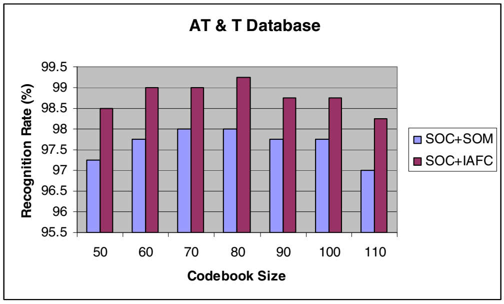

Fig. 5. Comparison of the recognition rate using AT & T database

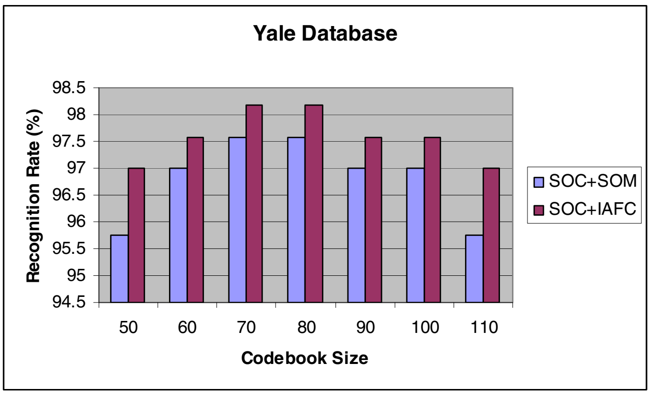

Fig. 6. Comparison of the recognition rate using Yale Face database

Experiments are also done by varying the values for the vigilance parameter, τ .The results are shown in figure 7. It is clear from the figure that for the value, τ =2, a higher recognition rate is achieved. In all the cases the codebook size is 80 and the value for σ is 0.5.

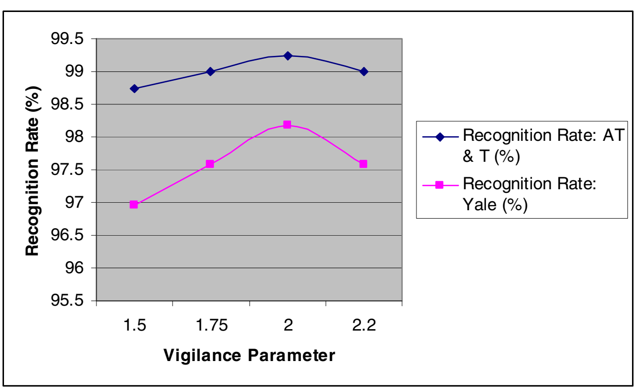

Fig. 7. Recognition rate for different values of τ

4.2 Experiments with Rejection Criteria

In complete absence of a rejection mechanism, all images presented to the recognition system, including images of unknown persons and background are mapped to the closest known face [10]. Reliably recognizing known persons while rejecting unknown persons is found to be a much more challenging task. Rejecting unknown faces means that the system has not only to accept wide variations in facial expression, head rotation, and so on, but also to reject patterns which lie quite close in the pattern space.

For the evaluation of the rejection performance of the system the databases are divided into two parts containing known faces and unknown faces. In the case of AT & T database, the 40 persons are divided into two parts containing 20 known faces and 20 unknown faces. So training is done with 100 images of the known 20 faces. The recognition and rejection performance of the system is then tested on all the 400 images of the database.

For verification a threshold was placed on the minimum distance between the histogram of the test face and the saved histograms in the database. Figure 8 shows False Acceptance Rate (FAR) and False Rejection Rate (FRR) plots for the verification experiment. An Equal Error Rate (ERR) of 3.5 % is achieved. In all these cases the codebook size is 80 and the value for the vigilance parameter, τ is 2.

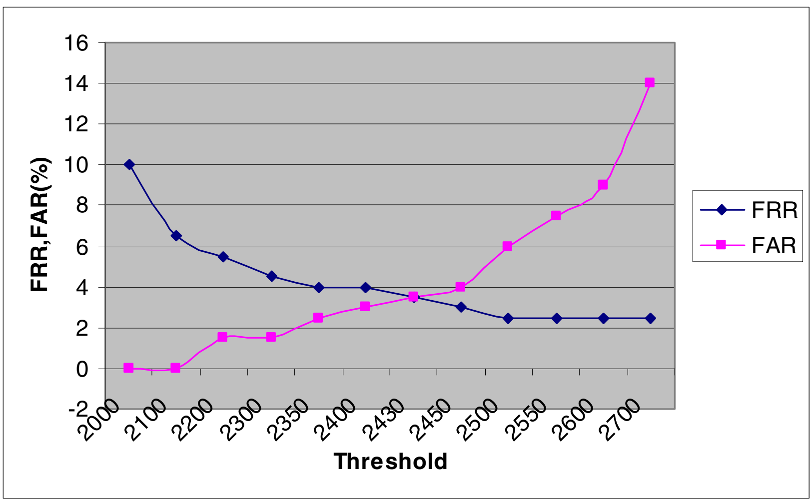

Fig. 8. False Acceptance Rate and False Rejection Rate (%) for AT & T database

Experiments are also done with the Yale database. In this case, 15 persons are divided into 8 known faces and 7 unknown faces. Training is done with 40 face images and testing is done with the all the 165 images in the database. Figure 9 shows False Acceptance Rate (FAR) and False Rejection Rate (FRR) plots for the verification experiment. An Equal Error Rate (ERR) of 6 % is achieved. In all these cases the codebook size is 80 and the value for the vigilance parameter, τ is 2.

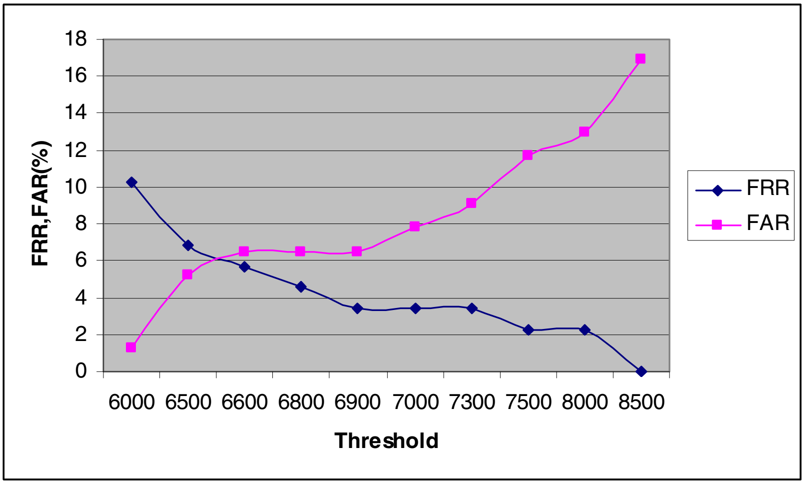

Fig. 9. False Acceptance Rate and False Rejection Rate (%) for Yale database

5 Conclusion

In this paper, a new face recognition system using vector quantization based on Integrated Adaptive Fuzzy Clustering (IAFC) is developed. A simple and efficient codebook design algorithm for face recognition using vector quantization is proposed. The codebook is created from two different codebooks. One codebook is created by code classification. The other codebook is created from the face images using Integrated Adaptive Fuzzy Clustering (IAFC). To create the codebook, the face images are divided into 2x2 blocks with a fixed codebook size. A good initial codebook is created from these blocks by code classification. The resultant initial codebook is combined with the codebook which is created by IAFC to become the final codebook. Utilizing such a codebook of size 80, a recognition rate of 99.25% is obtained for the AT & T database. For codebook sizes 70 and 80, a recognition rate of 98.18 % is obtained for Yale database. The results are more efficient than the existing method which consists of an optimized codebook with systematically organized codebook and Kohonen's SOM. For practical applications of face recognition, not a simple recognition rate but a False Acceptance Rate (FAR) and a False Rejection Rate (FRR) are more important. Rejection rate is calculated for obtaining the FAR and FRR. An Equal Error Rate (ERR) of 3.5 % and 6 % is obtained for AT & T and Yale database respectively.

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