INTERNATIONAL JOURNAL OF ELECTRONICS; MECHANICAL and MECHATRONICS ENGINEERING Vol.2 Num.2 pp.(166-171)

ERROR PROTECTION OF PCA BASED FACE RECOGNITION FOR TRANSMISSION OVER NOISY CHANNELS

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Abstract: *In this paper, we have proposed a system for reliable communication of coded grayscale facial images over noisy channels. Principle Component Analysis (PCA) is used for face dimensional reduction and face recognition and Repeated Bit Representation (RBR) is proposed to code the eigenfaces for mobile communication applications. Recognition obtained with RBR system approach reaches to %82 for 80 test images (2 poses per person) and 320 training images (8 poses per person) of ORL, by considering only the most important 30 coefficients of principle components in a noisy channel with SNR=-2dB.*

Keywords: PCA; Majority Voting; Repeated Bit Representation; Image Communication

1. INTRODUCTION

Image communication is an important research area which has many applications such as communications, geosciences and remote sensing, and remote security systems. One of the bases of image communication is image coding which is used for compressing images in order to obtain a low dimension representation of image for achieve inexpensive image communication and image storage. There are many different methods of image coding aiming at efficient and error free image communication systems with improvement in image coding as well as in communication techniques [1, 2]. In this paper, an eigenfaces technique is used for image coding and dimensionality reduction. Eigenfaces technique is one of the most frequently used methods based on PCA which transforms high dimensional data into a low dimensional space [3, 4]. In this paper, PCA is used not only for dimension reduction but also for recognition purposes. Binary Phase Shift Keying (BPSK) is used for the modulation of eigenvectors transmitted over AWGN channels. Transmitting coded images is more sensitive to error than a single pixel because the whole entry of representation vector carries much more image information than a single pixel [5]. Hosic et al. [6] have shown that all of the representation coefficients of PCA coded images have the same importance when transmitted over the noisy channels. They showed that integer and sign part of each PCA coefficient represent the "important" information and needs to be protected.

One of the most frequently technique which is used for protecting sourcecoded data is convolutional codes. Complicated convolutional codes perform better than the simple one but are more expensive in terms of implementation [7]. In this work, repeated bit representation (RBR) is implemented for coding PCA-coded face images. In PCA, a face space is decomposed into a small set of characteristic feature images called eigenfaces, and when linearly combined, represent a single face [8].

This work is organized in the following way: the next section reviews PCA based face recognition system; RBR is introduced and discussed in section 3. Experimental results are reported in section 4, and the last section is allocated for conclusion.

2. PCA BASED FACE RECOGNITION SYSTEM

Principal component analysis or Karhunen-Loève transformation [9] is standard technique used in statistical pattern recognition and signal processing for data reduction and feature extraction [10]. As the pattern often contains redundant information, mapping it to a feature vector can get rid of this redundancy and yet preserve most of the intrinsic information content of the pattern. These extracted features have great role in distinguishing input patterns. A face image in 2-dimension with size $N \times N$ can also be considered as one dimensional vector of dimension N^2. For example, face image from ORL (Olivetti Research Labs) database [11] with size 112 × 92 can be considered as a vector of dimension 10,304, or equivalently a point in a 10,304 dimensional space. An ensemble of images maps to a collection of points in this huge space. Images of faces, being similar in overall configuration, will not be randomly distributed in this huge image space and thus can be described by a relatively low dimensional subspace. The main idea of the principle component is to find the vectors that best account for the distribution of face images within the entire image space. These vectors define the subspace of face images, which we call "face space". Each of these vectors is of length N^2, describes an $N \times N$ image, and is a linear combination of the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face-like in appearance, it is referred as "eigenfaces" [3].

Let the training set of face images be $\Gamma_1, \Gamma_2, \ldots, \Gamma_M$, then the average of the set is defined by

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \Gamma_n \tag{1}$$

Each face differs from the average by the vector

$$\Phi_i = \Gamma_i - \Psi \tag{2}$$

This set of very large vectors is then subject to principal component analysis, which seeks a set of M orthonormal vectors, U_m, which best describes the distribution of the data. The k[th] vector, U_k , is chosen such that:

$$\lambda_k = \frac{1}{M} \sum_{n=1}^{M} \left(U_k^T \Phi_n \right)^2 \tag{3}$$

is a maximum, subject to:

$$U_I^T U_k = \delta_{Ik} = \begin{Bmatrix} 1, & if \ I = k \\ 0, & otherwise \end{Bmatrix} \tag{4}$$

The vectors U_k and scalars λ_k are the eigenvectors and eigenvalues, respectively of the covariance matrix:

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T = AA^T \tag{5}$$

where the matrix A is $[\Phi_1 \ \Phi_2 \ldots. \Phi_M]$.

The covariance matrix C, however is $N^2 \times N^2$ real symmetric matrix, and calculating the N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes. We need a computationally feasible method to find these eigenvectors. Consider the eigenvectors v_i of A^TA such that:

$$A^T A v_i = \mu_i v_i \tag{6}$$

Multiplying both sides by A, we have:

$$AA^T A v_i = \mu_i A v_i \tag{7}$$

where we see that Avi are the eigenvectors and μi are the eigenvalues of C= A AT. Following these analysis, we construct the M × M matrix L= ATA, where Lmn=□mT□n, and find the M eigenvectors, vi , of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces UI:

$$U_I = \sum_{k=1}^{M} v_{Ik} \Phi_k \ , \quad I = 1,....,M \tag{8}$$

With this analysis, the calculations are greatly reduced, from the order of the number of pixels in the images (N2) to the order of the number of images in the training set (M).

The eigenface images calculated from the eigenvectors of L span a basis set that can be used to describe face images. Sirovich and Kirby evaluated a limited version of this framework on an ensemble of 115 images (M = 115) images of Caucasian males digitized in a controlled manner, and found that 40 eigenfaces (M' = 40) were sufficient for a very good description of face images [12]. In practice, a smaller M' can be sufficient for identification, since accurate reconstruction of the image is not a requirement. In the framework of face recognition, the operation is a pattern recognition task rather than image reconstruction. The eigenfaces span an M' dimensional subspace of the original N^2 image space and hence, t*he* M' significant eigenvectors of the L matrix with the largest associated eigenvalues, are sufficient for reliable representation of the faces in the face space characterized by the eigenfaces.

A new face image (Γ) is transformed into its eigenface components by a simple operation as follows:

$$w_k = U_k^T (\Gamma - \Psi) \tag{9}$$

for k = 1,...,M'. The weights form a projection vector shown in equation (10), describing the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images.

$$\Omega^T = [w_1 \ w_2 .... w_{M'}] \tag{10}$$

The projection vector is then used in a standard pattern recognition algorithm to identify which of a number of predefined face classes, if any, best describes the face. The face class□k can be calculated by averaging the results of the eigenface representation over a small number of face images of each individual. Classification is performed by comparing the projection vectors of the training face images with the projection vector of the input face image. This comparison is based on the Euclidean distance between the face classes and the input face image. This is given in equation (11). The idea is to find the face class k that minimizes the Euclidean distance.

$$\varepsilon_k = \left\| \left(\Omega - \Omega_k \right) \right\| \tag{11}$$

where Ω_k is a vector describing the kth faces class. While for perfect reconstruction of the face image all the coefficients may be needed, for recognition, only the most significant coefficients play an important role. The coefficients consist of integer and fraction parts. In this paper, we propose that the integer part has a more significant role in recognition, and the experimental results show that if we consider more than 10 coefficients for recognition purposes we will get reasonable good recognition rate. The proposed system reduces the number of bits required for representation of the coefficients, because there is no need to spend any extra bits to represent the fraction part. Fig. 1 shows the recognition rates for 80 test images (2 poses per person) and 320 training images (8 poses per person) of ORL database [11], evaluated for different number of coefficient using the PCA method. The performance curve of the recognition rate saturates at %95 after 30 coefficients have been used in recognition. The recognition rate will not vary a lot by increasing the number of coefficients. The Minimum number of coefficients required for successful recognition rates, depends on the characteristics of data used in the training set.

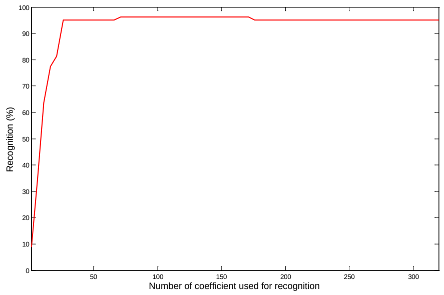

Figure 1 PCA based faces recognition for ORL face database

3. REPEATED BIT REPRESENTATION

Transmitting all the pixels of an image at a time requires a large bandwidth and a large bit rate, which in practice is usually not available. Therefore, a compressed form of the data should be sent over the channel. This may be a coded image where the amount of information per bit is substantially increased. Hence, a single bit error may result in a considerable decrease in performance [13]. One way to protect bits is to increase redundancy of the signal and make it less susceptible to the effects of mobile channels. However, although coded images contain compressed information, protecting all of it would not be practical. Applying Repeated Bit Representation (RBR) is an efficient technique which reduces overall redundancy by simply reducing the required bit representation of each represented coefficient. In this paper, PCA is used for image coding, where coded information for each image is carried in its projection vector. Most significant coefficients in the vector make a higher contribution in the representation of the faces. However, this property of projection coefficients and eigenfaces cannot be used efficiently in noisy channels due to the randomness of the noise and uneven contribution of the error on each coefficient [6, 14]. For example, after transmission, small coefficients originally with almost no contribution may become large and can even have a different sign. Therefore, all representation coefficients must be protected accordingly. As Hocanin et al. have shown [14], the errors in the fractional part of each coefficient do not result in considerable representation change compared to errors in integer or sign part. After every coefficient is transformed into a sequence of binary digits, it is enough to protect the first few bits representing the sign and the integer parts of each coefficient. According into the proposed system the most significant bits belong to the integer part of the coefficient and none of the fraction part will be transmitted. For encoding purposes each coefficient has been represented as a signed binary number. The most significant bit represents the sign of the coefficient. As the eigenfaces coefficients are within the range of (-15 , 15) so 5 bits are enough to represent the signed coefficient in binary format. After modulating the bit streams, each bit has been represented with three bit where each bit is equal to the value of the original bit as shown below:

$$\alpha_1\alpha_2\alpha_3\alpha_4 \rightarrow \alpha_1\alpha_1\alpha_1\alpha_2\alpha_2\alpha_2\alpha_3\alpha_3\alpha_3\alpha_4\alpha_4\alpha_4 \qquad (12)$$

After encoding, all bits are transmitted over the channel. At the receiver side, coded bit streams are decoded by using the majority voting principle. As bit ari, the ith received bit, is equal to the most repeated bit.

$$\alpha_{ri} = \mathrm{mod}\{\alpha_{ri1}, \alpha_{ri2}, \alpha_{ri3}\} \qquad (13)$$

This RBR method is applied on a bit level and protects all the coefficients in the projection vector, providing sufficiently small bandwidth and transmission Eb/N0. Received and decoded projection vectors are used for face recognition purposes, using the proposed PCA decoding algorithm. Increasing the number of repetition of the bits will lead to higher protection. The RBR method for proposed PCA, in terms of required bit to protect the coefficients, is even more efficient than [14], where unequal error protection (UEP) method was used for PCA. Table 1 shows the required bit number for different numbers of coefficients.

The required number of bits for the proposed method is significantly less than the required number of bits reported in [14] where UEP and equal error protection (EEP) are used.

Table 1 Number of required bit to transmit an image using UEP, EEP, and proposed RBR

Number of coefficient	UEP rate ¼ +rate ½ using PCA [14]	EEP rate 1/3 using PCA [14]	**RBR using integer coefficients of PCA**
20	2840	3840	**300**
30	4260	5760	**450**
100	14200	19200	**1500**
320	45440	61440	**4800**

4. REPEATED BİT REPRESENTATION

The transmission channel consists of AWGN and Rayleigh fading. The recognition has been evaluated for different SNR values. As Fig. 2 shows the recognition rate approximately stays the same when the SNR is 0 dB when there are 80 test images and 320 training images of ORL face database. So the proposed method, where only integer part of eigenfaces coefficients were transmitted, has performed well in terms of recognition and protection of the PCA-codes compare to the previous works [9]. This is quite significant as it clearly shows that less number of bits is required in order to represent the PCA coefficients as there is no need to keep the floating point values.

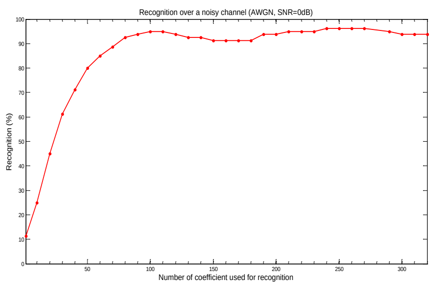

Figure 2 Recognition rate (%) of face images for different coefficient when SNR = 0dB

For better demonstration of the effect of SNR of the performance of the proposed system, Fig. 3 has been shown. In Fig. 3 the number of coefficients is kept fixed (30 coefficients) and the SNR value has been changed from -10dB to 10dB.

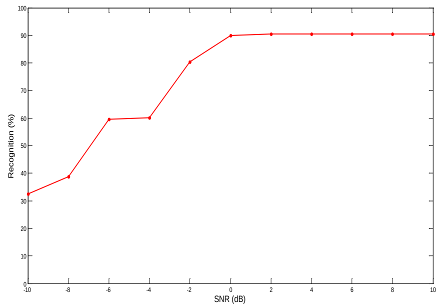

Figure 3 Recognition Rate (%) of face images for different SNR values using 30 coefficients

In this paper we introduced an error protection method for PCA based face recognition system. In order to reduce the required bit representation of the eigenfaces coefficient, the integer part of the coefficient was selected. The RBR has been used for protecting the eigenfaces coefficients from the effect of noise which exists in the communication channel. The required bit number for representing the coefficient are significantly reduced compared to similar work using UEP and EEP and also the recognition rate of the transmitted coefficients are very encouraging.

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