Unequal Error Protection Using Convolutional Codes for PCA-Coded Images

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Abstract. Image communication is a significant research area which involves improvement in image coding and communication techniques. In this paper, Principal Component Analysis (PCA) is used for face image coding and the coded images are protected with convolutional codes for transmission over Additive White Gaussian Noise (AWGN) channel. Binary Phase Shift Keying (BPSK) is used for the modulation of digital (binarized) coded images. Received binarized coded images are first decoded by the convolutional decoder using the Viterbi algorithm and then PCA decoded for recognition of the face. Unequal error protection (UEP) with two convolutional encoders with different rates is used to increase the overall performance of the system. The recognition rate of the transmitted coded face images without any protection is 35%, while equal protection with convolutional codes gives rates up to 85% accuracy. On the other hand, the proposed UEP scheme provides recognition rates up to 95% with reduced redundancy.

1 Introduction

Image communication is becoming increasingly important for diverse applications such as mobile communications, biomedical imaging, remote security systems etc. Hence, image communication problems are the focus of most recent scientific research, aiming efficient and error-resilient image communication systems with improvement in image coding as well as in communication techniques.

In this paper, eigenfaces technique is used for image coding. It is one of the most frequently used methods based on PCA which maps high dimensional data into a low dimensional space, saving memory and time [1]. PCA-coded images are used for image compression, recognition and transmission. BPSK is used for the modulation of image representation vectors transmitted over an AWGN channel. Transmitting coded images is predisposed for high errors at the receiver side since every entry of representation vector carries much more image information than a single pixel. Therefore, it is very important to minimize errors due to channel noise. Employing UEP on particular bits of the transmitted coefficient increases the overall system performance.

Convolutional codes are frequently used to protect source-coded data by adding redundant bits to it. Complicated convolutional codes perform better than the simple ones but require much more processing power and expensive circuitry. In order to satisfy performance and implementation requirements, in this paper, UEP is implemented such that a few most significant bits (i.e. first 7 bits) are encoded with low-

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rate convolutional codes while the remaining bits are encoded with a relatively simpler encoder (i.e. rate ½ encoder). Fig. 1 shows a general block diagram of the system.

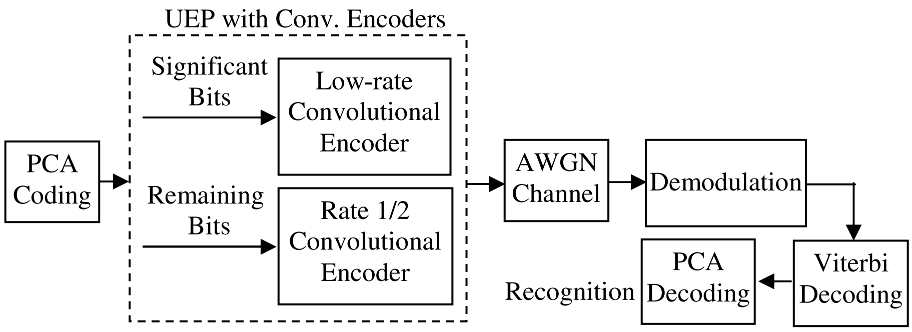

Fig. 1. Block Diagram of the System

The main idea in PCA is to decompose a "face space" into a small set of characteristic feature images called "eigenfaces", which, when linearly combined represent one single face. Every eigenvector (eigenface), has a different eigenvalue which determines its contribution in representation of a face image [1]. Eigenvectors with larger eigenvalues have the highest contribution in representation while the effect of others is not so significant, especially if the number of eigenfaces is large [2]. In order to implement identification process for the large data set, data compression is necessary.

In this paper, section 2 describes the eigenfaces approach in detail. Section 3 discusses the transmission of the projection vectors and unequal error protection of representation coefficients. Most significant bits of each coefficient are encoded by convolutional codes with lower rate (with more redundancy) while the rest of the bits are encoded at a higher rate. Projection vectors are then sent over the AWGN channel. Using this UEP scheme, important information that affects face recognition the most is highly protected. Received coded images are decoded first by the Viterbi algorithm. Then PCA decoding is used which includes the recognition of the face. Section 4 includes the results of simulations and the conclusions are stated in section 5.

2 Principal Component Analysis

Eigenface method is based on the linear PCA where a face image is encoded to a low dimensional vector. All face images are decomposed into a small set of characteristic feature images called eigenfaces. Each face image is projected on the subspace of meaningful eigenfaces (ones with the nonzero eigen-values). In this way, the collection of weights describes each face. Recognition of a new face is performed by projecting it on the subspace of eigenfaces and then comparing its weights with corresponding weights of each face from a known database.

2.1 Calculating Eigenfaces

Suppose that all face images in database are of the same size $w \times h$. Eigenfaces are obtained as eigen-vectors of the covariance matrix of the data points.

Let Γ_i be an image from the collection of M images in database. Face image is a 2-dimensional array of size $w \times h$, where w and h are width and height of the image, respectively. Each image can be represented as a vector of dimension wh and the average image, Ψ, is defined as:

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} (\Gamma_i) \; . \tag{1}$$

Each image, Γ_i, differ from the average image Ψ by the vector $\Phi_i = \Gamma_i - \Psi$.

The difference vectors are used to set up the covariance matrix C, as shown below [4].

$$C = \frac{1}{M} \sum_{i=1}^{M} \left(\Phi_i \Phi_i^T \right) = \Lambda \Lambda^T \, . \tag{2}$$

$$\Lambda = \left[\Phi_1 \Phi_2 \Phi_3 ... \Phi_M \right] . \tag{3}$$

Since there are M images in database, the covariance matrix C has only M-1 meaningful eigenvectors. Those eigenvectors, u_l , can be obtained by multiplying eigenvectors, v_l , of matrix $L=\Lambda^T \Lambda$ (of size $M \times M$) with difference vectors in matrix Λ [4].

$$u_l = \sum_{k=1}^{M} v_{lk} \Phi_k \; . \tag{4}$$

The eigenvectors, u_l, are called the eigenfaces [4]. Eigenfaces with higher eigenvalues contribute more in representation of the image. Therefore such eigefaces are used for construction of the “face subspace” for image projections which are employed in face identification, classification or recognition. Projection (representation) vectors for every image are defined as

$$\Omega = [\omega_1 , \omega_2 , \dots , \omega_M]. \tag{5}$$

ω_k is the k^{th} coordinate of the image Φ in the face subspace and is calculated as [4]:

$$\omega_k = u_k^T (\Gamma_k - \Psi), \quad k=1, \dots, M. \tag{6}$$

The projection (representation) vectors are indispensable in face recognition tasks, due to their uniqueness.

2.2 Recognition

As mentioned above, the projection vector, Ω, is necessary for reconstruction and recognition of the image. Euclidian distance between representations of two different images (Ω_1 and Ω_2) is used for the determination of the recognition rate.

$$E = \sqrt{\sum_{i=1}^{M} \left(\omega_{1i} - \omega_{2i}\right)^2} \,. \tag{7}$$

While for perfect reconstruction of the face image all the coefficients may be needed, for recognition only the most significant ones play an important role. Figure 2 shows recognition rates for 80 test images (2 per person) and 320 training images (8 per person) evaluated for different number of coefficients used. In the system described above (8 poses for each person) recognition rate saturates at 95% after 10 coefficients have been used in recognition. The same rate is obtained even if all 320 representation coefficients were used. This implies that it is enough to use only a certain number of most significant coefficients with larger corresponding eigen-values in order to have the maximum recognition rate. Minimum number of coefficients, required for successful recognition rates depends on the data used in training as well as the test images.

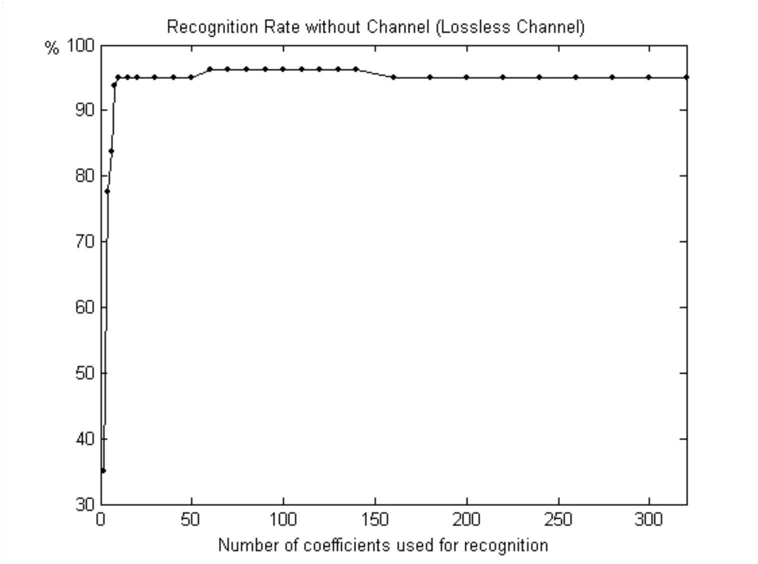

Fig. 2. Recognition Rate versus the number of coefficients used for recognition

3 UEP Using Convolutional Codes for PCA Coded Images

Transmitting all the pixels of an image at a time requires a huge bandwidth and a large bit rate, which in practice is not available. Therefore, concentrated and compressed form of data should be sent over the channel in order to meet consumer requirements. This compressed form of data may be a coded image where amount of information per bit is substantially increased. Hence a single bit error may result in considerable decrease in performance [3].

In this paper, PCA is used for image coding, where coded information for each image is carried in its projection (representation) vector. Most significant coefficients in the vector are shown to have higher contribution in representation of the face. Unfortunately, this property of projection coefficients and eigenfaces cannot be used in noisy channels due to randomness of the noise and unequal ratio of the error on each coefficient. For instance, small coefficients originally with almost no contribution, after transmission may become large and can even have a different sign. Therefore it is important to protect least significant coefficients just like the most significant ones in transmission of projection vectors. One way to protect bits is to increase redundancy of the source signal and make it less susceptible to the effects of AWGN channel. This is successfully done by convolutional codes where the code rate determines the amount of redundancy.

3.1 UEP of Projection Coefficients Using Convolutional Codes

Protecting all coefficients would require larger bandwidth and delay which would not allow much improvement as compared to pixel transmission. Fortunately, errors in the fractional part of each coefficient will not result in considerable representation change compared to errors on integer or sign part. Since every coefficient is transformed into a sequence of binary digits, it is enough to protect a first few bits representing the sign and the integer parts of each coefficient. The most significant bits are hence encoded using a low rate convolutional code with more redundant bits and noise resilience and the remaining bits are encoded with a simple rate 1/2 convolutional code [4]. After encoding, all bits are modulated and transmitted over AWGN channel. At the receiver side, coded bit streams are decoded by the corresponding convolutional decoders. The UEP method is applied on bit level and protects all the coefficients in the projection vector, providing sufficiently small bandwidth and transmission Eb/N_0.

Simulations are performed to assess the performance of the UEP scheme. Projection vectors are binarized using a 64 bit quantizer, where the most significant 5 bits represent the integer part and the sign of the coefficient and the remaining 59 are used for the fractional part. This particular arrangement of the bits depends on the nature of the data used in simulations and it can be varied to meet specific requirements. The maximum value of the coefficients is 16 and hence 4 bits are assigned for integer part and an additional bit is assigned for the sign. After projection vectors are digitized, UEP method is applied on a bit level. As previously mentioned, bits which correspond to the sign and the integer part are encoded using a lower rate convolutional encoder while a simpler, rate 1/2 encoder is used for the remaining bits. In the simulations, 7 bits are protected with a lower rate covolutional code in order to increase performance even more. Those received coefficients are used for recognition of the face (Fig. 1).

4 Results and Discussion

400 face images from ORL face database are used in this work (10 various poses for 40 different persons) where 320 images (8 per person) are used for training and 80 (2 per person) for testing [5]. Eigen-subspace is constructed from 320 training images and the remaining 80 test images are only used in recognition analysis.

Convolutional codes used for the simulation have rates 1/2, 1/3 and 1/4. The most important criterion for optimal codes is maximizing *minimum free distance* d_{free}, which determines the error correction capability of the code and determines performance at high Eb/N_0 values. The second criterion is minimizing the number of *nearest-neighbors*, Ad_{free} whose influence increases as the Eb/N_0 decreases [6]. The codes used in the simulations are chosen to satisfy the both criteria. The results for performance analysis are based on comparison of recognition rates for transmitted coded images with:

- UEP using rate 1/4 + rate 1/2 convolutional code
- UEP using rate 1/3 + rate 1/2 convolutional code
- All bits equally treated using: rate 1/2, rate 1/3 and rate 1/4.

Performance of above mentioned models are also examined for 8-state and 32-state convolutional codes.

4.1 Face Recognition of 80 Received Coded Images (Projection Vectors)

Projection vectors of 80 test images are transmitted over the channel with AWGN. These vectors are received with errors, decreasing recognition rate significantly. Performance is better for higher values of average Eb/N_0 but the aim is to keep Eb/N_0 as low as possible. Applying previously described UEP, encoding the first 7 bits of each coefficient with a low rate convolutional code, provides significant increase in performance. By this way number of redundant bits is not very high and performance is satisfactory. Furthermore, recognition rates approach the ideal case even for the relatively small values of Eb/N_0.

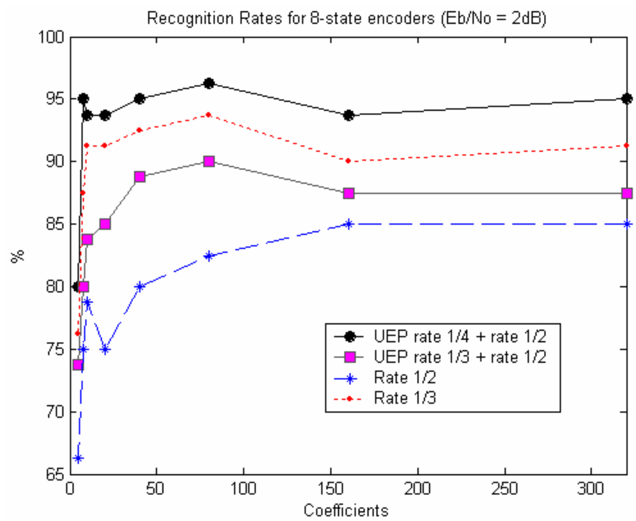

Fig. 3. Recognition Rate with and without UEP for 8-state encoders at 2dB

Fig. 3 and 4 compare the performance of the systems with 8-state and 32-state convolutional encoders in AWGN, with and without UEP for Eb/N_0=2dB, respectively. Without UEP and for low rate encoders, the number of encoded bits becomes large, increasing the data rate requirements. UEP reduces the number of bits for transmission, providing satisfactory results at a low Eb/N_0.

In Fig. 3, it is seen that at a low value of Eb/N_0 = 2dB, *UEP rate 1/4 + rate 1/2* scheme increases recognition rate by approximately 5% compared with the *equal rate 1/3* encoding for all bits. This is true even though the UEP scheme has a lower redundancy. For each coefficient, the UEP system results in $7\cdot 4 + 57\cdot 2 = 158$ bits while the *Rate 1/3* code requires $64 \cdot 3 = 192$ bits. In order to improve recognition performance, more complicated convolutional codes may be used. Fig. 4 shows that the increasing number of states of the encoders does not provide further performance gains.

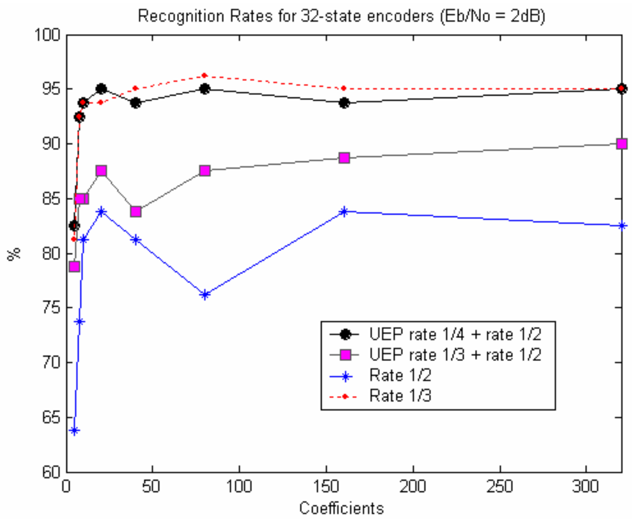

Fig. 4. Recognition Rate with and without UEP for 32-state encoders at 2dB

5 Conclusion

Coefficients of PCA-coded images, when transmitted over a noisy channel, are all equally important for image representation. Therefore protecting the first few bits of each coefficient is more useful than only protecting coefficients with higher corresponding eigenvalues. Error correcting codes used to protect these coefficients must be carefully chosen to minimize the effects of the channel without increasing the added redundancy. It is shown that the proposed UEP scheme increases overall system performance for face recognition at low Eb/N_0 values. Face recognition rates for the UEP with rate 1/4 + rate1/2 Convolutional Codes reaches recognition rates up to 95% and is higher than that of the equal protection with a rate 1/3 convolutional code. This is especially important considering that the UEP scheme requires much less redundancy. Increasing the complexity of the convolutional codes with larger number of encoding states does not result in considerable increase in recognition performance. The proposed scheme may be efficiently employed for face recognition in adverse channel conditions where Eb/N_0 is low with minimal added redundancy for error protection.

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