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# UNEQUAL ERROR PROTECTION OF PCA-CODED FACE IMAGES FOR TRANSMISSION OVER MOBILE CHANNELS

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## ABSTRACT

*In this paper, a system for reliable communication of coded grey-level face images over noisy channels is proposed. Principal Component Analysis (PCA) is used for face image coding and an unequal error protection (UEP) joint source channel coding scheme is proposed for mobile communication applications. Coded images are protected with convolutional codes for transmission over mobile channels. Recognition rates obtained with UEP system approach the 95% recognition performance for images from the ORL face database.*

## 2. INTRODUCTION

Image communication is a significant research area focusing in many applications, such as mobile communications, biomedical imaging, and remote security systems. The main purpose of image coding is to compress images for two specific tasks, inexpensive image communication and image storage. Over the years, many different algorithms for image coding were developed, all aiming at 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, transmission and recognition. Binary Phase Shift Keying (BPSK) is used for the modulation of image representation vectors transmitted over AWGN and Rayleigh fading channels. Transmitting coded images is prone to high errors 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.

One of the approaches to protect coded images is to divide the transmitted bit stream into the “important” and “less important” bits, depending on the effects of the channel [2]. It is shown in [3] that all of the representation coefficients of PCA coded images have the same importance when transmitted over the noisy channels. The integer and sign part of each PCA coefficient represent the “important” information and needs to be protected [3].

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 [8]. In order to satisfy performance and implementation requirements, in this paper UEP is implemented where a few most significant bits (i.e. first 7 bits) are encoded with low-rate convolutional codes while the remaining bits are encoded with a relatively simpler encoder (i.e. rate ½ encoder) [3]. Fig. 1 shows a general block diagram of the system.

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. Every eigenvector (eigenface), has a different contribution in representation of a face image [1]. Eigenvectors with larger eigenvalues have higher contribution whereas the effect of others is lower, especially if the number of eigenfaces is large [4]. In order to implement the identification process for the large data set, data compression is necessary.

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

## 3. PCA BASED EIGENFACES METHOD

Eigenfaces method is based on 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 nonzero eigenvalues). Hence, 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.

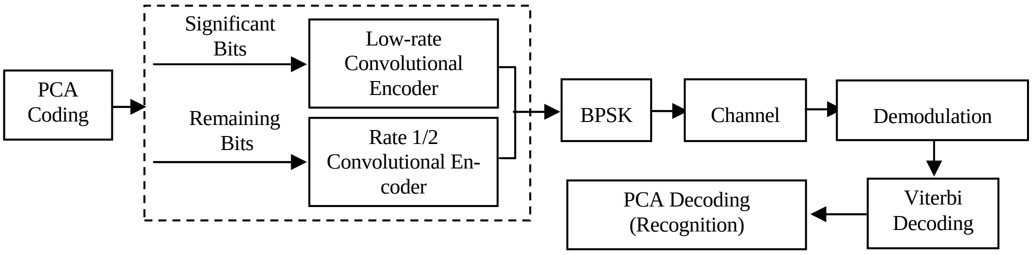


Fig. 1. Block Diagram of the System.

### 3.1. Calculating Eigenfaces

Assume that all face images in a database are of the same size $w\times h$. Eigenfaces are obtained as the eigen-vectors of the covariance matrix of the data points. Let $\Gamma_i$ be an image from the collection of $M$ images in the database. A 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 $w\times h$ and the average image, $\Psi$, is defined as:

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

Each image, $\Gamma_i$ , differ from the average image $\Psi$ by the difference vector, $\Phi_i = \Gamma_i - \Psi$. The difference vectors are used to set up the covariance matrix $C$, as shown below [1].

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

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

Since there are $M$ images in the 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 $\Lambda$ [1].

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

The eigenvectors, $u_l$, are called the eigenfaces [1]. Eigenfaces with higher eigenvalues contribute more in representation of a face image. Therefore such eigenfaces are used for the construction of the “face subspace”, which are employed in face identification, classification or recognition. The face subspace projection vector for every image is defined by,

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

where $\omega_k$ is the $k^{th}$ coordinate of the image $\Phi$ in the face subspace and is calculated as in [1] by,

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

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

### 3.2 Face Recognition

The projection vector, which represents a given face image in the eigenspace can be used for the recognition of faces. Euclidian distance, $\varepsilon$, between projection vectors of two different images ($\Omega_1$ and $\Omega_2$) is used to determine if a face is recognized correctly or not.

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

While for perfect reconstruction of the face image all the coefficients may be needed, for recognition, only the most significant coefficients play an important role. Fig. 2 shows recognition rates for 80 test images (2 poses per person) and 320 training images (8 poses per person) evaluated for different number of coefficients used. The performance curve of the 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 eigenvalues in order to have the maximum recognition rate. Minimum number of coefficients required for successful recognition rates, depends on the characteristics of data used in training set.

## 4. UEP USING CONVOLUTIONAL CODES

Transmitting all the pixels of an image at a time requires a huge 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 [5]. 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 unequal error protection is an efficient technique which reduces overall redundancy. 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 have higher contribution in representation of the faces [1]. 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 [3].

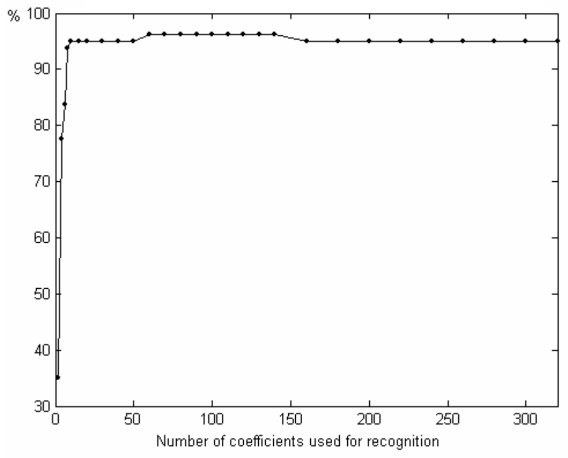


Fig. 2. Recognition Rate versus the number of coefficients used.

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 shown in [3], 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. 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 higher rate 1/2 convolutional code [6]. After encoding, all bits are modulated and transmitted over the channel. At the receiver side, coded bit streams are decoded by the corresponding Viterbi decoders. This UEP method is applied on a bit level and protects all the coefficients in the projection vector, providing sufficiently small bandwidth and transmission $E_b/N_0$. Received and decoded projection vectors are used for face recognition purposes, using the PCA decoding algorithm.

The projection vectors are binarized using a 64 bit uniform quantizer, where the most significant 5 bits represent the integer part and the sign of the coefficient whereas the remaining 59 are used for the fractional part. This particular arrangement of the bits depends on the nature of the data used and can be adjusted to meet specific requirements. The maximum value of the coefficients is observed to be 16 and hence 4 bits are assigned for integer part and an additional 1 bit is assigned for the sign. After projection vectors are binarized, 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 (i.e. 1/3 or 1/4) convolutional encoder while a simpler, rate 1/2 encoder is used for the remaining bits. Additionally, 7 most significant bits are protected with a lower rate convolutional code in order to increase performance even further.

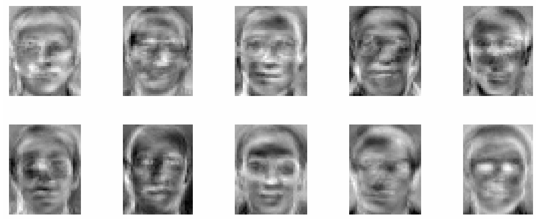

Fig. 3. Eigenfaces with the highest eigenvalues.

## 5. RESULTS AND DISCUSSIONS

In this paper, 400 face images from ORL face database [7] are used (10 various poses for 40 different persons), where 320 images (8 poses per person) are used for training and 80 (2 poses per person) for testing. Eigen-subspace is constructed from 320 training images and the remaining 80 test images are only used in recognition analysis. The following figure shows the first 10 eigenfaces with the highest corresponding eigenvalues of the 320 faces from the training set.

Convolutional codes used in the simulations are all 8-state codes and have rates 1/2, 1/3 and 1/4. One of the most important criterion for the choice of the codes is maximizing *minimum free distance* $d_{free}$, which determines the error correction capability and the performance at high $E_b/N_0$ values. The second criterion is minimizing the *number of nearest-neighbors*, $Ad_{free}$ which becomes more important as $E_b/N_0$ decreases [8]. The codes used in the simulations are chosen according to these criteria. Table 1 gives details about the codes used, where $m$ is the memory order, g is the generator sequence, $d_{free}$ is the minimum free distance, and $Ad_{free}$ is the number of nearest neighbors.

Table 1. Parameters of the rate R convolutional codes used in the simulations.

| Rate $R$ | $m$ | $g^{(0)}$ | $g^{(1)}$ | $g^{(2)}$ | $g^{(3)}$ | $d_{free}$ | $Ad_{free}$ |
|---|---|---|---|---|---|---|---|
| 1/4 | 3 | 13 | 13 | 15 | 17 | 13 | 2 |
| 1/3 | 3 | 13 | 15 | 17 | - | 10 | 3 |
| 1/2 | 3 | 13 | 17 | - | - | 6 | 1 |

The performance analysis is based on the comparison of the recognition rates for transmitted coded images with UEP using rate 1/4 + rate 1/2 convolutional code and all bits equally protected (Equal Error Protection-EEP) using rate 1/3 convolutional code. In the simulations, only 200 (out of 320) coefficients for all 80 test images are transmitted over the channel and used for recognition purposes. When the UEP scheme is used, for each coefficient 142 bits (7×4+57×2) are transmitted, where 78 (142-64) bits are the additional ones used for protection of 64 original data bits. On the other hand, with EEP with rate-1/3 convolutional codes, 192 bits are transmitted over the channel for each coefficient, where 128 the bits are redundant. Thus the difference in redundancy per coefficient for UEP and EEP methods is 50 bits. Table 2 summarizes the number of transmitted bits for UEP and EEP methods. The proposed system performance is examined for 8-state

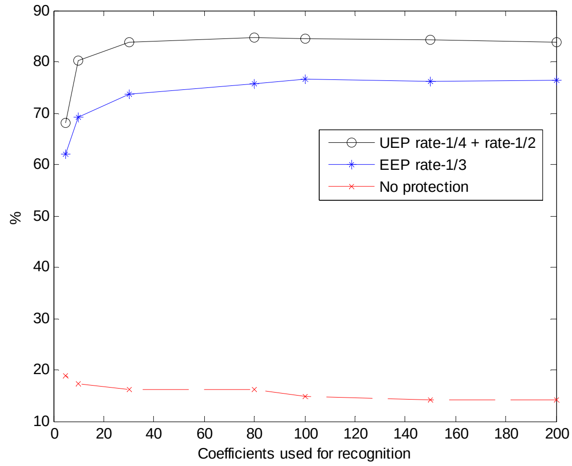


Fig. 4. Recognition rates for AWGN channel, $E_b/N_0$ = 0 dB.

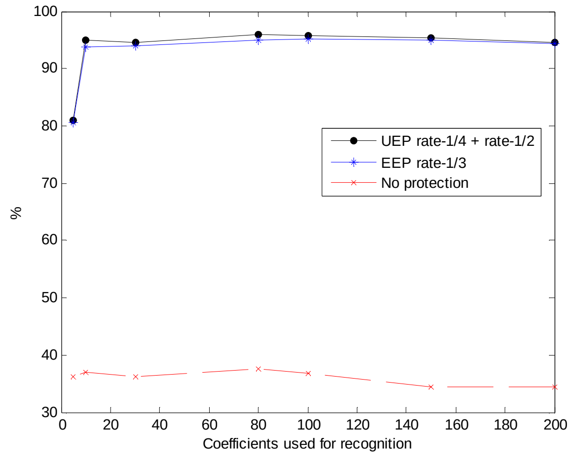


Fig. 5. Recognition rates for AWGN at $E_b/N_0$ =3 dB.

convolutional codes for different $E_b/N_0$ values. It can also be shown that applying 32-state convolutional codes with more complexity does not improve the performance significantly [3].

Table 2. Redundant bit reduction using UEP vs EEP.

| Number of Transmitted bits | | UEP rate-1/4 + 1/2 | | EEP rate-1/3 | |
|---|---|---|---|---|---|
| | | Total | Redundant | Total | Redundant |
| Bits per coefficient | 64 | 142 | 78 | 192 | 128 |
| Coefficients per image | 200 | 28,400 | 15,600 | 38,400 | 25,600 |
| Transmitted images | 80 | 2,272,000 | 1,248,000 | 3,072,000 | 2,048,000 |

## 5.1 Face Recognition of 80 Received Coded Images

Projection vectors of 80 test images are transmitted over the AWGN and Rayleigh fading channels. These vectors are received with errors, decreasing the recognition rate significantly. Performance is better for higher values of average $E_b/N_0$ but the aim is to keep $E_b/N_0$ as low as possible and still achieve satisfactory recognition rates. Applying the UEP, encoding, the first 7 bits of each coefficient with a low rate convolutional code, provides significant increase in performance. In this scheme, the number of redundant bits is not very high and performance is satisfactory. Furthermore, the recognition rates approach the case for error-free transmission even at relatively small $E_b/N_0$ values.

### *5.1.1 Performance over AWGN Channel*

Figure 4 shows the recognition rates for AWGN channel at $E_b/N_0$ = 0 dB, for UEP, EEP and transmission without any protection of the projection vectors. Recognition rates for no protection fall from 95 percent to less than 20 percent and saturate at 15 percent when more than 100 coefficients are used. Applying EEP, by using rate-1/3 convolutional codes for all the bits of each coefficient, the performance increases, from about 15 percent to 75 percent. On the other hand, the UEP method improves the recognition rates by an additional 10 percent, approaching 85 percent. Although UEP method uses less redundant bits than EEP, it still performs better and provides higher recognition rates at $E_b/N_0$=0 dB.

Figure 5 shows the performance under the same conditions at $E_b/N_0$= 3 dB. Naturally, as signal energy increases, recognition rates for all schemes increase accordingly. This is confirmed in fig. 5 for the system without any protection (dashed line marked with ×) where the recognition rates increase about 20 percent when Eb/N0 increases from 0 to 3 dB. Performance of the EEP approaches to that of the UEP as the signal energy increases. The results show that the proposed UEP method outperforms EEP method at low $E_b/N_0$ values, while it provides approximately the same recognition rates at higher $E_b/N_0$ values. In addition to better performance at low transmission energy, more important advantage of UEP method is that it uses considerably fewer redundant bits.

### *5.1.2Performance over Rayleigh Multipath Fading Channel*

The following assumptions are made in the simulation of the multipath Rayleigh fading channel model: The carrier frequency $f_c$ is 900 MHz, the mobile is assumed to move at a speed of 30 km/h which gives maximum Doppler frequency to be $f_m$=25 Hz. The signal is composed of 5 Rayleigh faded paths and the paths are the delayed faded versions of the original signal by uniform delay with the period $\Delta T$=5. Since fading channel contains memory, convolutional codes are especially suited for error protection. In the simulations, 8 state convolutional codes are used with the same UEP and EEP schemes. One of the important characteristics of the fading channels is that increasing signal energy will not necessarily improve the performance significantly which is unlike the case for the AWGN channel. This is due to delay and multipath effects. However, increasing $E_b/N_0$, affects the difference in performance between the UEP and the EEP protection schemes. As expected, increasing signal energy brings closer the recognition rates obtained by the UEP and those obtained by the

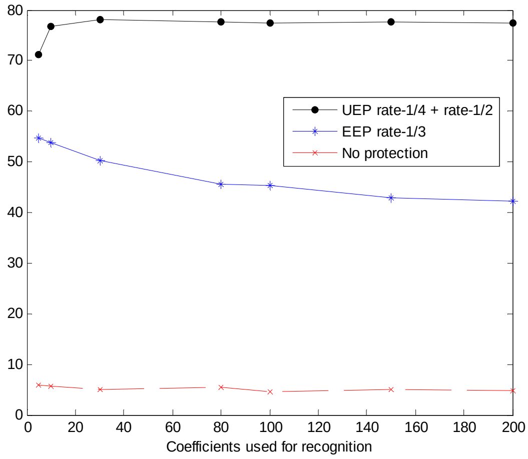


Fig. 6. Recognition rates for Rayleigh fading, $E_b/N_0$= 0 dB.

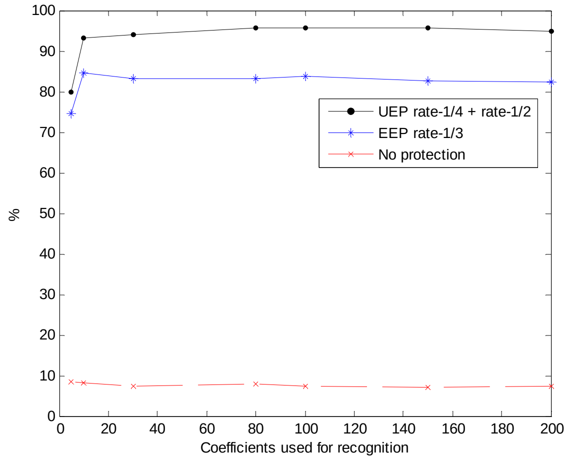


Fig. 7. Recognition rates for Rayleigh fading, $E_b/N_0$= 3 dB.

EEP. The UEP scheme clearly outperforms the EEP even at $E_b/N_0$= 5 dB, which was not the case in the AWGN channel.

Figure 6 shows that at $E_b/N_0$= 0dB, recognition rates for the UEP method are almost 80 percent, while the EEP has the lower performance of about 45 percent. Due to fading, the overall system performance is decreased compared to AWGN channel. However, the recognition rates for the UEP scheme exceed those of the EEP by a much higher margin.

Fig. 7 presents the recognition rates for the Rayleigh fading channel at $E_b/N_0$= 3 dB. The performance for no protection is shown to be around 10 percent, which shows that higher $E_b/N_0$ values do not increase system performance over fading channels. Nevertheless, performance of the UEP and EEP schemes increase with increasing $E_b/N_0$. The difference in performance becomes smaller, but the UEP scheme outperforms the EEP at all $E_b/N_0$ values. Even though fading severely affects system performance, the UEP scheme offers close to the ideal recognition rate of 95% (error-free channel). This is not the case for the EEP scheme even though more redundancy is used.

## 6. CONCLUSION

In this paper, a system for the reliable communication of coded grey-level face images over noisy channels is proposed. PCA is used for face image coding and an UEP channel coding scheme is proposed for transmission over mobile channels.

The system performance is evaluated by using the transmitted face projection vectors for face recognition. The proposed UEP scheme outperforms EEP method at low $E_b/N_0$ values, while providing the same recognition rates at higher $E_b/N_0$ values in AWGN channel. It is important to note that the increase in performance even though less redundancy is used for error control coding. The scheme is also evaluated in Rayleigh fading channel where the UEP method offers almost ideal recognition rates, 95%, at $E_b/N_0$=3dB. Even though more redundancy is used, the EEP scheme cannot attain these recognition rates at the same $E_b/N_0$. The relative improvement in performance of the proposed UEP scheme is much more pronounced in fading channels. In mobile communication channels, where signal fading pose severe challenges, the proposed system offers a viable alternative for image transmission.

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