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Pattern Recognition Using Feature Feedback: Application to Face Recognition

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Abstract: In this paper, we propose a new pattern recognition method using feature feedback and present its application to face recognition. Conventional pattern recognition methods extract the features employed for classification using PCA, LDA and so on. On the other hand, in the proposed method, the extracted features are analyzed in the original space using feature feedback. Using reverse mapping from the extracted features to the original space, we can identify the important part of the original data that affects the classification. In this way, we can modify the data to obtain a higher classification rate, make it more compact or abbreviate the required sensors. To verify the applicability of the proposed method, we apply it to face recognition using the Yale Face Database. Each face image is divided into two parts, the important part and unimportant part, using feature feedback, and the classification performed using the feature mask obtained from feature feedback. Also, we combine face recognition with image compression. The experimental results show that the proposed method works well.

Keywords: Feature feedback, feature extraction, face recognition, feature mask, region differential JPEG compression.

1. INTRODUCTION

Pattern recognition has received much attention due to its theoretical challenges as well as applications in face recognition [1-3], finger print recognition [7] and gas recognition [8,9]. As a result, numerous methods have been developed for pattern recognition in the last few decades. Several pattern recognition methods have been proposed to reduce the dimensionality of the input data sample [4,5,10,11]. In order to improve the classification rate, conventional feature extraction methods such as PCA [2] and LDA [11], new features were constructed from the input data samples based on statistics and the input samples projected onto a lower dimensional feature space.

On the other hand, most real world problems involve a very large number of input variables, e. g., there are tens of thousand of pixels in an image. In many cases, it is intractable and redundant to use all of the pixels for image recognition. Therefore, if it is possible to analyze the importance of each input variable, the recognition process can be performed more effectively and the recognition results can be improved.

Considering these facts, there have been studies into the problem of selecting pixels in image recognition. Pang *et al.* [14] proposed a discriminant pixel selection method using Gabor-LDA [18]. Kokiopoulou and Frosssard [15] formulated the sampling process as a supervised feature selection problem. In [16], discriminant pixels are selected based on the order vector obtained from NLDA [6].

In this paper, we propose a new pattern recognition method using feature feedback and present its application to face recognition. We generalize the feature selection method through reverse mapping from the feature space to the input space. Moreover, in order to use the image data more efficiently in terms of the size of the data, we combine an image compression method with face recognition.

First, we classify the images using the pixels selected from the feature mask which is obtained using feature feedback. By mapping the extracted features into the input space, we can evaluate the relative importance of the information contained in each variable (pixel in an image) for the classification. To accomplish this, we analyze the relation between the basis of the feature space and the input variables. We first extract the useful features from a face image by linear discriminant analysis [3]. Then, we distinguish the feature-related region in the face image using feature feedback. We obtain the feature mask from the feature-related region and use it to classify the images.

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Next, we compress the images according to the relative importance of pixels and use the compressed images to perform face recognition. The feature-related region, which is an important part of the classification, is compressed with high-image quality and the other region is compressed with low-image quality. Through this adaptive compression based on JPEG [19], we can reduce the size of the image and enhance the important part simultaneously. This is advantageous in highdimensional data management such as data acquisition, saving, processing and transmission. Finally, the compressed face image is classified using an appearance based recognition approach. Through experiments, we show that while the storage size of the resultant data is reduced, the recognition rates are better than those obtained using the original data.

The rest of this paper is organized as follows. In Section 2, we briefly overview related works. Feature feedback is explained in Section 3, and its application to face recognition is presented in Section 4. The experimental results are described in Section 5, followed by the conclusion in Section 6.

2. RELATED WORKS

2.1. Principal component analysis (PCA)

Given an image sample with dimensions of $n_r \times n_r$, the image can be represented as a point in the n-dimensional vector space where $n = n_r \times n_r$. This vector space is normally called an input space or an image space. Since an image space is generally a high dimensional space, handling image samples directly incurs a considerable computational burden. The PCA (Principal Component Analysis) method is one of the most popular and widely used methods and is very useful in reducing the dimension of an original space to a manageable size [2]. Let us consider a set of N image samples, $\{x_1, x_2, \cdots, x_N\}$, taking values in n-dimensional image space. Then, PCA finds the best set of projection vectors in the sample space that will maximize the total scatter across all images. The objective function of PCA is written as the following:

$$W_{PCA} = \arg\max_W \left| W^T S_T W \right|, \tag{1}$$

where $S_T = \sum_{i=1}^{N} (x_i - \mu)(x_i - \mu)^T$ is the total scatter matrix and μ is the total mean of the whole training set. The columns of W_{PCA}, $\{W_{E1}, W_{E2}, \cdots, W_{Em}\}$ are the projection vectors, which are called eigenfaces.

2.2. Linear discriminant analysis (LDA)

Linear discriminant analysis (LDA) was originally developed for supervised learning, especially for classification and recognition problems, and to find the optimal linear discriminating functions. Then, LDA searches for those vectors in the underlying space that best discriminate among the classes. This is achieved by maximizing the determinant of the between-class scatter matrix (S_b) and minimizing the determinant of the within-class scatter matrix (S_w) simultaneously [3]. This means that those samples that belong to the same class are concentrated in a small area while each class is located far apart from the other classes. The objective function of LDA can be written as follows:

$$W_{LDA} = \arg\max_W \left| \frac{W^T S_b W}{W^T S_w W} \right|. \tag{2}$$

Let the training set contain $\boldsymbol{c}$ classes and each class cihave N_i samples. Then, S_b and S_w are defined as:

$$S_b = \sum_{i=1}^{c} (\mu_i - \mu)(\mu_i - \mu)^T,$$
$$S_w = \sum_{i=1}^{N} \sum_{x_k \in \{c_i\}} (x_k - \mu)(x_k - \mu)^T, \tag{3}$$

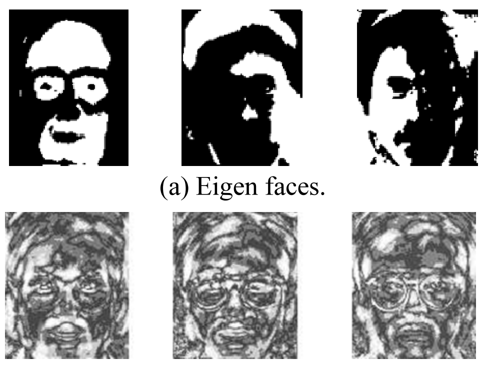
where μ_i is the mean of class c_i, and x_k is a sample belonging to class. W_{LDA} is the set of generalized eigenvectors of S_b and S_w corresponding to the m largest generalized eigenvalues, and it can be computed from the eigenvectors of $S_w^{-1} S_b$. Note that there are at most $c-1$ nonzero generalized eigenvalues, so the upper bound on m is $c - 1$. However, since the dimension of the input space (n) is usually much larger than the number of available samples (N), S_w in (3) becomes singular, which is known as the "small sample size (SSS) problem" [10]. In order to avoid this SSS problem, we first perform the PCA to reduce the dimension of the input space to the rank of S_w ($N - c$), and then apply LDA to reduce the dimension to $m \ll n$ (PCA + LDA) [3]. Consequently, $W_{PCA+LDA}$ is given by:

$$W^T_{PCA+LDA} = W^T_{LDA} W^T_{PCA}, \tag{4}$$

where

$$W_{LDA} = \arg\max_W \left| \frac{W^T W^T_{PCA} S_b W_{PCA} W}{W^T W^T_{PCA} S_w W_{PCA} W} \right|. \tag{5}$$

The columns of $W_{PCA+LDA}$ are the projection vectors, which are called fisherfaces. Then, the feature vector $y_k \in R^m$ can be defined by the following linear



(a) Eigen faces.

(b) Fisher faces.

Fig. 1. Feature vectors.

transformation:

$$y_k = W^T_{PCA+LDA} + \mathrm{x}_k = [w_{F1}, w_{F2}, \cdots, w_{Fm}]^T \mathrm{x}_k, \quad k = 1, 2, .., N \tag{6}$$

where the columns of $W_{PCA+LDA}$, $\{w_{F1}, w_{F2}, \cdots, w_{Fm}\}$ are the basis of the feature space. Fig. 1 shows the eigenfaces and fisherfaces obtained from the Yale Face Database [17] by PCA and PCA+LDA, respectively.

3. FEATURE FEEDBACK

We first extract the features from a set of image samples, and then feed them back to the image samples again. Based on the feedback information, each sample is differentiated into two regions: the important and unimportant regions.

Each value of $\{x_{ki} \mid i = 1, 2, .., n\}$ of an image sample x_k represents the gray intensity value of the *i*-th pixel of the image. Let $w \in R^n$ be the projection vector obtained by the feature extraction method described in Section 2, and w can be an eigenface or fisherface. Let $\alpha_i \in R^n$ be the *i*-th unit coordinate vector of the input space. Then, x_k and the *l-th* eigenvector (*l* = 1,2, ..,*m*) can be expressed by a linear combination of the unit direction vectors, $\{\mathrm{a}_1, \mathrm{a}_2, \cdots, \mathrm{a}_n\}$, in the *n*-dimensional input space as follows:

$$x_k^T = \{x_{k1}, x_{k2}, \cdots, x_{kn}\} = x_{k1}\mathrm{a}_1 + x_{k2}\mathrm{a}_2 + .. + x_{kn}\mathrm{a}_n,$$
$$w_l^T = \{w_{l1}, w_{l2}, \cdots, w_{ln}\} = w_{l1}\mathrm{a}_1 + w_{l2}\mathrm{a}_2 + .. + w_{ln}\mathrm{a}_n.$$

Each component of w_l, w_{li} (*i* = 1,2, ..,*n*) acts as a role of a reference to divide the image into two different regions. The value of w_{li} is the amount of weight added to the *i*-th direction in the input space for the purpose of constructing w_l. That is, the absolute magnitude of w_{li} indicates how much the *i*-th direction in the input space contributes to constructing the basis of the feature space w_l. Therefore, when the value of w_{li} is larger than the predefined threshold *T*, the region that contains the *i*-th component (the *i*-th pixel in the case of an image) is regarded as an important region, while the remaining region is regarded as unimportant.

We first distinguish an important region using the first eigenface (w_{E1}) with the largest eigenvalue. As shown in Fig. 2, by distinguishing the region based on the PCA that best represents the sample scatter, most non-face regions such as background and some regions relatively unrelated to sample scatter are removed. We set a threshold T_E to an average value of $\|w_{E1i}\|$s. Fig. 2 shows images whose regions are classified into two regions according to the corresponding $\|w_{E1i}\|$ values. In Fig. 2, the white pixels are regarded as being more important than the black ones in the eigenface. Then, in order to obtain regions in a face image which are useful for classification, we select pixels based on fisherfaces (w_{Fl}). Likewise, we can identify the important regions according to each fisherface. By merging each of the important regions, we can get the final 'Maskface' or 'Feature Mask', which are the important regions for classification.

Fig. 2. Segmented images using feature feedback.

The detailed feature feedback procedure can be summarized as follows:

Step 1: Using PCA, useful features to represent data scatter are extracted. We divide the first eigenface into two parts, *EI* and *EU*. Here, *EI* and *EU* are regarded as important and unimportant parts based on the components (w_{E1i}) of an eigenface, respectively. Then, we can segment the first eigenface as follows:

$$\begin{cases} w_{E1i} \in EI, & \text{if } \|w_{E1i}\| \geq T_E \\ w_{E1i} \in EI, & \text{otherwise}, \end{cases} \tag{7}$$

where T_E is set to an average value of w_{E1i} s. By using (7), we obtain the segmented eigenface *EI*.

Step 2: Using PCA+LDA, discriminant features are extracted. Taking into consideration eigenvalue distribution, we select m_f fisherfaces corresponding to the m_f largest eigenvalues. We divide each fisherface into two parts, FI_l and FU_l. Here, FI_l and FU_l are regarded as important and unimportant parts in the lth fisherface, respectively. Let us define T_{Fl} as a threshold value of *l*-th fisherface. Then, we can segment the *l*-th fisherface as follows:

$$\begin{cases} w_{li} \in EI, & \text{if } \|w_{li}\| \geq T_{Fl} \\ w_{li} \in EI, & \text{otherwise}. \end{cases} \tag{8}$$

By using (8), we obtain the segmented fisherfaces $FI_1, FI_2, \cdots, FI_{m_f}$

Step 3: We construct the 'Maskface' or 'Feature Mask' with the mf segmented fisherfaces FI_1, FI_2, $\cdots, FI_{m_f}$. The 'Feature Mask' *FI* is obtained using the following equation:

$$FI = \alpha_1 FI_1 + \alpha_2 FI_2 + \cdots + \alpha_{m_f} FI_{m_f}, \tag{9}$$

where $\alpha_i (i = 1, .., m_f)$ is the weight for each fisherface.

Step 4: We perform the classification using *FI*.

The performance of classification using the proposed method depends on the number of fisherfaces m_f, thresholds T_{Fl}, and the merging scheme for *FI*. The selection of those parameters also depends on the applications.

4. APPLICATION TO FACE RECOGNITION

In this section, we apply the proposed method to face recognition. The features used for feature feedback at the feedback stage are obtained by PCA and PCA + LDA metnods. First, we construct the feature mask following the procedures described in the previous section. In the classification stage, a test image is classified using this feature mask. Also, an image compression method is applied on the feature masking image for face recognition.

4.1. Face recognition using feature feedback

As shown in Fig. 3, we first construct the feature mask using feature feedback. Then, the features for face recognition are extracted from the masking images. The detailed procedure for face recognition using feature feedback is as follows:

Step 1: After obtaining the segmented images using *EI* by (7), PCA+LDA is used to extract the discriminant features for feature feedback at the feedback stage. Among the $c-1$ fisherfaces produced by PCA+LDA, we select the fisherfaces which will be used in the feature feedback based on the distribution of eigenvalues in Fig. 4. In this paper, we use the three fisherfaces corresponding to the three largest eigenvalues.

Step 2: We divide each fisherface into two parts, FI_l and FU_l. Here, FI_l and FU_l are regarded as important and unimportant parts in the l-th fisherface, respectively. Let us define al and *T* as the average value of kwlik and a threshold value, respectively. Then, we can segment the l-th fisherface as follows:

$$\begin{cases} w_{li} \in FI_l, & \text{if } \|w_{li}\| \geq \alpha_l + T \\ w_{li} \in FU_l, & \text{otherwise.} \end{cases} \tag{10}$$

By using (10), we obtain the segmented fisherfaces FI_1, FI_2 and FI_3 as shown in Fig. 3.

Step 3: We construct the final feature mask with the three segmented fisherfaces. Using the OR operation, we can obtain the feature mask, as shown in Fig. 3. The white pixels in the feature mask can be thought of as the important pixels in the face images for the classification:

$$FI = FI_1 + FI_2 + FI_3. \tag{11}$$

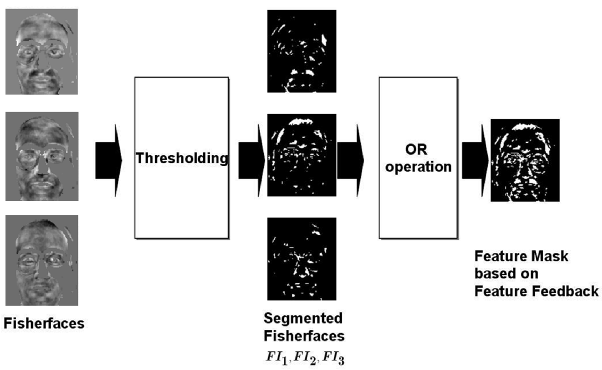


Fig. 3. Segmentation using threshold for fisherfaces.

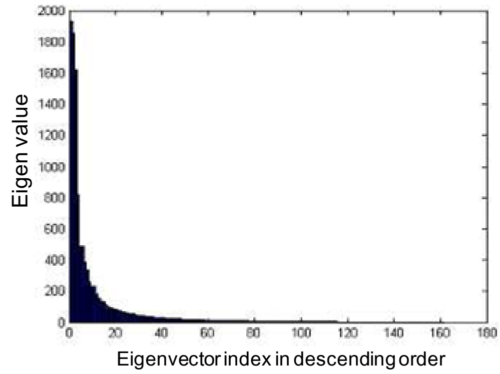


Fig. 4. Eigenvalues in descending order.

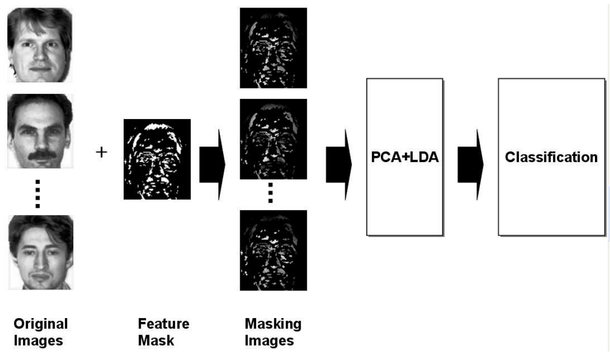


Fig. 5. Eigenvalues in descending order.

Step 4: We perform the classification as shown in Fig. 5. The selected pixels obtained using the feature mask are utilized as the input of the classification.

Those pixels that are important for the classification can be selected in the form of a feature mask. Only the pixels selected by the feature mask will be used in the classification. This may improve the performance of the classification as shown in the experiments in Section 5.

4.2. Face recognition using feature feedback

In this subsection, we present region-differential JPEG compression using feature feedback. Based on the feature mask, the important region for the classification is compressed with high-quality while the rest is compressed with low-quality. Compression with locally different qualities is effective for data storage and transmission, because the important information is preserved, while redundant information is discarded. Through region-differential JPEG compression, the bits per pixel (bpp) can be reduced.

As shown in Fig. 6, to compress the facial images with JPEG [19], the images are blocked with 8×8. The important part is compressed with high image quality and the other part is compressed with low image quality. Following this, the classification is performed using the

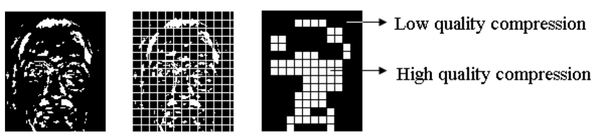
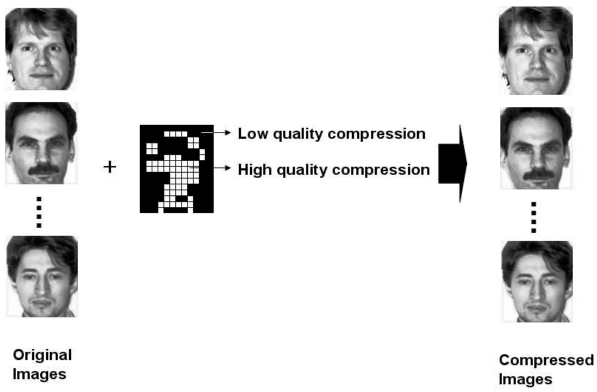
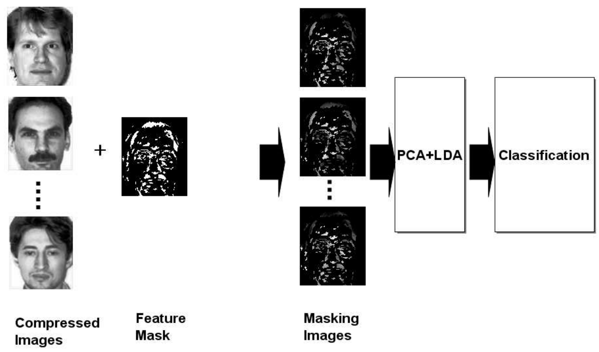


Fig. 6. Blocked images and differrential compression.



(a) Region differential JPEG compression.



(b) Classification with compressed images.

Fig. 7. Region differential JPEG compression and classification.

same feature mask as that used in Step 3. Fig. 7 shows the entire classification process using region differential JPEG compression.

5. EXPERIMENTAL RESULT

5.1. Face recognition using feature feedback

We applied the proposed method to the Yale Face Database [17] to evaluate its performance. The Yale Face Database contains 165 gray images of 15 individuals, gathered with different facial expressions, with or without glasses, and under different lighting conditions. The center of each eye was manually located and the eyes were rotated so as to be aligned horizontally, as in [18]. Each face image was cropped and rescaled so that the center of each eye is placed at a fixed point in an image of 120×100 (pixels). Then, histogram equalization [12] is applied to the rescaled image,and the resulting pixels are normalized to have zero means and unit variances [13]. Fig. 8(a) shows 11 examples of Yale Face Database images under various conditions.

(a) Zoom-out images.

(b) Zoom-in images.

Fig. 8. Cropped and rotated images f yale database.

The 11-fold cross validation [10] was used to evaluate the performances for the Yale Face Database. In this scheme, one image from each subject was randomly selected for testing, while the remaining images were used for training. In other words, there were 150 images in the training set and 15 images for probing. This experiment was repeated 11 times, so that every image appeared once in each probe set. For the classification, the PCA+LDA method was used as the feature extraction method and the nearest neighbor rule was used as a classifier with the *L*2 distance metric. It is noted that PCA+LDA method is well known, but is not necessarily the best one.

The selection of a good feature extraction method is beyond the scope of this paper; our focus is only on the effectiveness of pixel selection, as demonstrated in the context of face recognition. Therefore, it is possible to use other feature extraction methods for classification [1,6,20] and the proposed method can be also applied to those methods.

Since the information in a face image is different for each zoom scale, the recognition performance also depends on how the image is cropped. Thus, we applied the proposed method to two image sets cropped with different zoom scales. The first image set, as shown in Fig. 8(a), consists of zoom-out images of the original images and the other set, as shown in Fig. 8(b), contains zoom-in images that are closely cropped, removing the background and hair.

For the experiment of the proposed method, we use the first three fisherfaces, and the image segmentation and classification are performed following the procedures described in Figs. 4 and 5, respectively. In order to find a suitable threshold *T*, we conducted the proposed method for different *T*'s. Table 1 shows the average classification rates for different dimensional feature spaces for each threshold *T*. From the results in Table 1, we selected the threshold values 0.011 for the zoomout images and 0.002 for the zoom-in images. Table 1 shows the recognition rates for different dimensional feature spaces for the original images I_{ori} and the masking images I_{mask} obtained by the proposed method. As can be seen in Table 2, for the zoom-out and zoom-in images I_{mask} gives about 4.0 % and 2.0 % better

Table 1. Classification using feature feedback for different T's.

Zoom-out images		Zoom-out images	
T	Average	T	Average
0.001	85.1	-0.0015	78.7
0.002	84.0	-0.001	78.3
0.003	84.3	-0.0005	78.8
0.004	84.9	0	78.7
0.005	8534	0.0005	79.1
0.006	87.0	0.001	78.6
0.007	87.1	0.0015	79.7
0.008	87.7	**0.002**	**80.4**
0.009	86.8	0.0025	79.7
0.010	87.6	0.003	79.7
0.011	**88.4**	0.0035	78.8
0.012	88.3	0.004	77.7

Table 2. Classification rates.

Features		1	2	3	4	5	6	7	8	9	10	11	12	13	14	average
Zoom-out	I_{ori}	38.8	53.9	70.3	83.0	85.5	90.9	92.1	95.2	93.9	94.6	95.2	95.8	96.4	97.0	84.5
	I_{mask}	40.6	67.9	80.0	87.3	90.9	92.7	95.8	95.8	95.2	96.4	97.6	100	98.8	99.4	88.4
	I_{com}	43.0	66.7	80.0	84.9	80.3	91.5	93.3	93.3	94.6	95.2	96.4	98.8	98.8	98.2	87.5
Zoom-in	I_{ori}	37.6	52.1	65.5	71.5	74.5	83.0	86.1	86.7	88.5	89.7	90.3	90.3	89.7	92.1	78.4
	I_{mask}	35.8	53.9	64.2	75.8	80.0	87.3	88.5	87.9	89.7	92.1	90.9	92.1	93.3	93.9	80.4
	I_{com}	35.8	52.7	63.6	75.2	79.4	87.9	87.3	89.1	80.3	91.5	92.7	93.3	93.9	94.6	80.5

average recognition rates than I_{ori} over the number of features, respectively.

5.2. Region differential JPEG compression (RDJC)

Fig. 9 shows the divided block regions for zoomout and zoom-in images. Table 3 shows the bpp (bits per pixel) for the images. When we use an 8 bit bmp, the bpp value is 8. For a JPEG, the bpp's are 2.125 and 1.897 for zoom-out images and zoom-in images, respectively. Using the region differential JPEG compression (RDJC), the bpp's of the images are 1.703 and 1.825, respectively.

Fig. 10 shows the images I_{com} with region differential JPEG compression. The PSNR (Peak Signal to Noise Ratio) for high-quality, low-quality and RDJC images

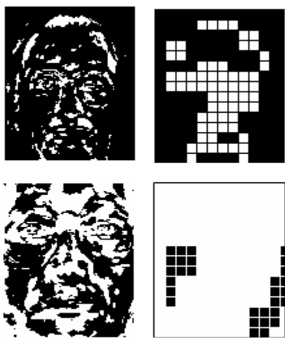


Fig. 9. Divided block regions.

Table 3. Comparison of bpp.

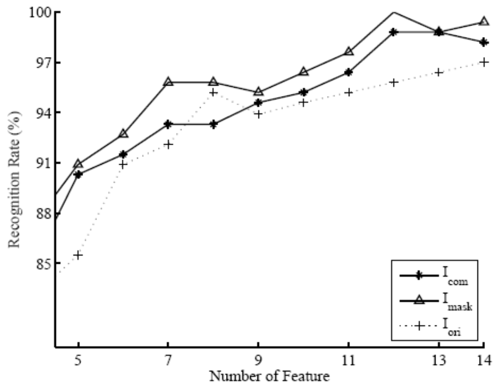
	Zoom-out images	Zoom-in images
BMP	8	8
JPEG	2.215	1.897
Proposed	1.703	1.825

(a) Example of high quality images(PSNR=36.4dB).

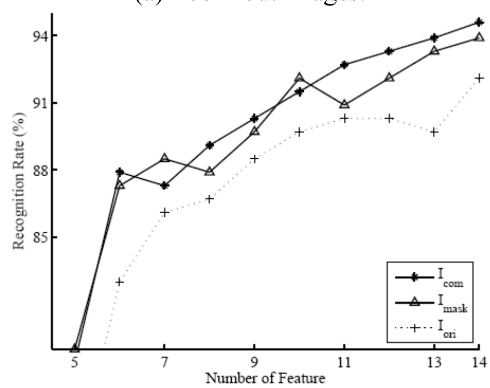
(b) Example of high quality images(PSNR=36.4dB).

(c) Example of high quality images(PSNR=36.4dB).

Fig. 10. Quality 75, quality 15 and RDJC images for zoom-out images.



(a) Zoom-out images.



(b) Zoom-in images.

Fig. 11. Recognition rates for a various number of features using differently compressed image.

for zoom-out images are 36,4, 29,3 and 30.4 dB, respectively. Fig. 11 shows the recognition rates, which are based on I_{ori}, I_{mask} and I_{com} for different numbers of features, respectively. As can be seen in Fig. 11, although the storage size of I_{com} become smaller than those of I_{ori} and I_{mask} through the regiondifferential compression, I_{com} consistently outperforms I_{ori} for almost all numbers of features and gives comparable recognition rates to I_{mask}.

6. CONCLUSIONS

In this paper, we proposed a new pattern recognition method using feature feedback and presented its application to face recognition. Generally, pattern recognition methods concentrate on the extraction of features. On the other hand, in this paper, we focus on the selection of the important part in the original domain. Using reverse mapping from the extracted features to the original space, we identify the important part in the original data which affects the classification. This makes us expect the improvement in recognition rates because the unnecessary information, which can be noise in the classification, is discarded. Using the proposed method, we can modify the data to obtain a higher classification rate, make the data more compact or abbreviate the required sensors from the sensor arrays. To verify the applicability of the proposed method, we applied it to face recognition based on the PCA+LDA method, and it can be also applied to other various feature extraction methods for classification problems. First, we select the feature related region in the face image using feature feedback and construct the feature mask using the feature-related pixels. Second, we perform face recognition using the pixels selected from the feature mask for each image. Furthermore, we proposed region differential JPEG coding to improve the efficiency. With the experimental results obtained using the Yale Face Database, we show that the classification rate becomes higher using the proposed method and the data rate can be reduced using RDJC.

In the proposed method, we require a more systematic algorithm for the determination of the threshold value, *T*, the number of fisherfaces and the merging scheme between the fisherfaces. These objectives remain as future work.

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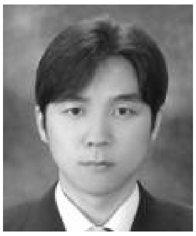

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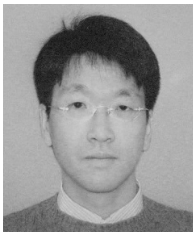

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