Face Recognition Using Composite Features Based on Discriminant Analysis

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ABSTRACT Extracting holistic features from the whole face and extracting the local features from the sub-image have pros and cons depending on the conditions. In order to effectively utilize the strengths of various types of holistic features and local features while also complementing each weakness, we propose a method to construct a composite feature vector for face recognition based on discriminant analysis. We first extract the holistic features and the local features from the whole face image and various types of local images using the discriminant feature extraction method. Then, we measure the amount of discriminative information in the individual holistic features and local features and construct composite features with only discriminative features for face recognition. The composite features from the proposed method were compared with the holistic features, local features, and others prepared by hybrid methods through face recognition experiments for various types of face image databases. The proposed composite feature vector displayed better performance than the other methods.

INDEX TERMS Composite feature, discriminant analysis, face recognition, feature selection, holistic-feature, local-feature.

I. INTRODUCTION

Recently, with the development of hardware technologies and the expansion of sofeware applications, technologies for various contents have emerged. In particular, the recent propagation of smart mobile devices facilitates the public interest in intelligent systems that exploit various machine learning techniques applicable to diverse image data. Among these technologies, face recognition is commonly used and can be applied in various fields including broadcast content, entertainment, access control, security, and surveillance [1]–[8]

Many algorithms for face recognition have been proposed. Depending on the necessary information extracted from certain images, the algorithms can be divided into the holistic-features-based method [9]–[12], the local-features-based method [13]–[15], and the hybrid method [16]–[20]. Such methods using holistic features such as Eigenface [9], Fisherface [10], Null space Linear Discriminant Analysis (LDA) [11], Eigenfeature Regularization and Extraction (ERE) [12], and Discriminant Discrete Cosine

Transform (D-DCT) [21] extract the necessary features from the whole image of a face using various linear transforms. In [22], multi-view dictionary learning and low-rank learning were applied to face recognition. In recent years, as research on deep learning has actively been conducted, face recognition methods using deep neural networks have been introduced [23]–[25]. The holistic features have the advantage of preserving texture or shape information that is useful for distinguishing faces. Many of the proposed holistic-features-based methods perform quite favorably for normalized face images obtained in a limited environment such as the inside of laboratories [1], [10], [11]. However, owing to variations in a face due to factors such as the wearing of accessories, hair style, changing expressions, and an uncontrolled environment involving camera pose or varying illumination, the recognition rate is significantly reduced by large distortion of the whole face image [1], [4], [15], [26], [27].

The local-features-based methods that extract features from the sub-images of a face have an advantage of being less sensitive to numerous variations than the

holistic-feature-based methods, although the information on the contours of entire faces cannot be used. That is, although a face with accessories may display varying pixels around the accessories, the sub-images with no accessories do not have such effects. The local-features-based methods are relatively less vulnerable to such variations than the holistic-features-based methods. However, the recognition performance significantly fluctuates depending on the face image portion. The method in [16] used the images of facial elements such as the eyes, nose, and mouth as sub-images based on the results obtained from psychophysical experiments that suggested the prominent facial components would contain more discriminative information. In [15], a discriminant-analysis-based method was proposed to select pixels for face recognition by quantitatively measuring the amount of the discriminative information of individual pixels constituting a face image.

Hybrid methods using the whole image of faces as well as their sub-images have been presented. The methods in [16] and [19] used the holistic features extracted from the whole image of a face and their local features extracted from the sub-images such as features of the eyes, nose, or mouth, as well as sub-images equally divided from the image of a whole face. In [18], the DCT transformation was applied to the whole image and its sub-images to extract the holistic and local features, respectively. The extracted features were then connected, and the Improved LDA (I-LDA) [28] was applied. In [19], [20], and [29], the Principal Component Analysis (PCA) [13] and the Gabor wavelet kernel were employed to extract the holistic and local features. Subsequently, the Adaptive Neuro-Fuzzy Inference System (ANFIS) [30] and the Support Vector Machine (SVM) [31] were adopted as algorithms to connect the extracted features.

This paper presents a method to construct a composite feature vector to utilize all advantages of various types of features for face recognition. No particular feature extraction method always outperforms other ones. Various types of holistic and local features have their own strengths in recognizing faces, but at the same time, each of them may exhibit different weaknesses depending on the type of variations or noise, which makes face recognition difficult. For example, some features are robust to illumination variations but are vulnerable to occlusion variations, while others exhibit the opposite characteristics. Since such features having different properties may be complementary to each other, instead of using an existing holistic or local feature extraction method, we evaluate the discriminative power of individual holistic or local features. Then, we select features only with the high discriminative power and construct the optimal composite features that are useful for face recognition. These composite features utilize the strong aspects of various features and at the same time compensate for their weakness, consequently providing more robust recognition performance to numerous types of variations. In the proposed method, since the extraction of holistic and local features is performed in parallel, there is no additional operation other than the module for evaluating individual features, which is performed

close to real time. In addition, the proposed method can be used to effectively combine newly developed feature extraction methods such as deep learning with existing methods. We have reported the results obtained from a recent study on the construction of composite features [32]. Here, we further improve these results, providing a more detailed analysis with extensive discussions, and present additional experimental results under various conditions.

To extract holistic features for face recognition, the face images are cropped equally according to the coordinates of the two eyes, where the local features were extracted from the sub-images created from the divided images [19] or those made by a feature selection method [15], [33]. The holistic and local features, used to construct the set of basic features, were extracted by employing the Null space LDA method [11] and were selected among discriminative feature extraction methods, because the Null space LDA and discriminative feature extraction methods perform favorably with high-dimensional data such as images. The power of class discrimination for each feature in the set of basic features was evaluated by using the input feature selection method based on discriminant analysis [33]. The composite features for face recognition were then constructed by selecting the optimal features based on this evaluation.

For the experiments conducted to determine the face recognition performance, the proposed method was applied to the FERET database [34], CMU-PIE database [35], Yale B database [36], and AR database [37], all of which have been frequently employed in previous studies as reference data for face recognition. From the experiments, the proposed method was found to be superior in face recognition to other hybrid methods, as well as to cases employing solely holistic or local features.

This paper is comprised of the following sections. In Section 2 describes not only the method used to construct both the whole and sub-images of a face, but also the methods used to extract the holistic and local features from the constructed whole and sub-images. Section 3 illustrates the construction of composite feature vectors from the measurement of class discrimination of the power of each feature to select the final features among the holistic and local features extracted for face recognition. The face recognition performance of the proposed method for various face image databases will be presented in Section 4. Section 5 concludes this paper.

II. EXTRACTION OF HOLISTIC AND LOCAL FEATURES
A. CONSTRUCTION OF THE WHOLE FACE IMAGE AND SUB-IMAGES
The face alignment step, which crops the face areas of various sizes in the image to the same size, is an important factor that greatly affects the final recognition performance of the face recognition system [26]. In this paper, the face image was rotated so that the two eyes are horizontal, based on their coordinates, and the image is rescaled to keep the distance between the eyes in all face images constant. To avoid the
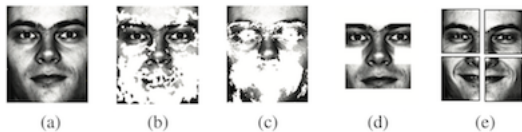
FIGURE 1. (a) $\mathbf{x}^H$, (b) $\mathbf{x}^{IVS}$ [15], (c) $\mathbf{x}^{FSDD}$ [33], (d) $\mathbf{x}^{ENM}$ [16], and (e) $\mathbf{x}^{SEG}$ [19]. Samples of a cropped full face image and several types of sub-images.

effects of hair style and background of an image on face recognition performance, the images were cropped to nearly equal sizes [4] (Fig.1). The performance of local features for face recognition has different characteristics depending on how the sub-image is constructed. Four types of sub-images were employed in this paper as shown in Fig. 1. $\mathbf{x}^{ENM}$ and $\mathbf{x}^{SEG}$ are the sub-images constructed by cutting partial areas of face images. The studies in the discipline of psychophysics [38], particularly delving into the process of how humans recognize faces of other people, as well as studies in the discipline of bioinformatics [16], [39] also examining human face recognition, commonly report that the relevant information concentrates on salient components such as the eyes, nose, and mouth. Based on results obtained from such studies, $\mathbf{x}^{ENM}$ resulted as the sub-image comprised of the eyes, nose, and mouth domains. Features could also be extracted by dividing the domain of the face regionally to relieve the effects of face recognition performance degradation by the distortion of face images attributable to factors such as illumination. $\mathbf{x}^{SEG}$ is a sub-image resulting from the domain of the face divided into four sub-domains from which the local-features were extracted [19].

Some pixels of a face image can also be selected to create sub-images. Considering the face recognition issue as a classification problem for image data, pixels with small variance in the same person's images in the feature space and large dispersion from other people's images are suitable for data classification. $\mathbf{x}^{FSDD}$ and $\mathbf{x}^{IVS}$ are the sub-images constructed by selecting pixels useful for face recognition based on these discriminant analyses. $\mathbf{x}^{FSDD}$ is the sub-image constructed with pixels of a larger discriminant distance [33] that represents the class discrimination power of individual pixels whereas $\mathbf{x}^{IVS}$ is the sub-image constructed with pixels having more discriminative information based on the magnitude of the linear discriminant elements of the feature vectors [15]. In this paper, the NLDA (Null space LDA) feature vectors were employed for the construction of $\mathbf{x}^{IVS}$. Around 50% of the total number of pixels of a whole face image were selected to make $\mathbf{x}^{FSDD}$ and $\mathbf{x}^{IVS}$. The respective two face images (fa, fb) of 200 subjects contained in the FERET database were used as training images to obtain the discriminant distance and NLDA feature vectors.

B. FEATURE EXTRACTION FOR FACE RECOGNITION
The LDA known as "Fisherface" for face recognition and the NLDA method which is effective especially for high-dimensional data such as image data and the ERE method

are the representative methods frequently employed for the extraction of features in face recognition. The NLDA method was used to extract the holistic and local features from the whole and sub-images of the face. Given that the training set consists of N samples and C classes, the between-class (S_B) and within-class (S_W) covariance matrices are defined in the following equations [10].

$$S_B = \frac{1}{N} \sum_{i=1}^{C} N_i (\mu_i - \mu)(\mu_i - \mu)^T$$

$$S_W = \sum_{i=1}^{C} \sum_{\mathbf{x}_m \in c_i} (\mathbf{x}_m - \mu_i)(\mathbf{x}_m - \mu_i)^T \qquad (1)$$

Here, $\mathbf{x}_m \in R^{n \times 1}$ denotes the mth image sample consisting of n pixels that belong to the class c_i, while μ_i and μ indicates the mean of samples belonging to the class c_i and the total mean of all samples, respectively. For the case of LDA, the projection vectors used as the basis of feature space are the eigenvectors of $S_W^{-1} S_B$ [40]. This implies that LDA constructs the feature space where the covariance between the means of respective classes would be maximized and the covariance within classes would be minimized in the range space of S_W ($W^T S_W W \neq 0$). However, with respect to the discriminant information, the null space of S_W (that is, the space that maximizes the value of $W^T S_B W$ by simultaneously satisfying the condition $W^T S_W W = 0$) would possess more discriminant information than the space that maximizes the value of $W^T S_B W$ by meeting the criterion $W^T S_W W \neq 0$ at the same time. Thus, NLDA projects samples onto the null space of S_W to concentrate the samples within a class on a point by using the objective function expressed in equation (2) and then attempting to search for the subspace consisting of the projection vectors that maximize the variance of S_B [11].

$$W_{Opt} = argmax_{|W^T S_W W| = 0} \left| W^T S_B W \right| \qquad (2)$$

In the NLDA feature space, the image sample is represented as the NLDA feature vector $\mathbf{y} = W_{Opt}^T \mathbf{x}$.

III. CONSTRUCTION OF A COMPOSITE FEATURE VECTOR BASED ON DISCRIMINATIVE INFORMATION MEASUREMENT
Let the sets of projection vectors obtained from the image of the whole face ($\mathbf{x}^H$) and sub-images ($\mathbf{x}^L$, $L \in \{IVS, ENM, FSDD, SEG\}$) by using NLDA be $W_{Opt}^H \in R^{m \times C-1}$ and $W_{Opt}^L \in R^{m \times C-1}$ respectively, then the vectors of the holistic and local features $\mathbf{y}^H = [y_1^H, y_2^H, .., y_{C-1}^H]^T$ and $\mathbf{y}^L = [y_1^L, y_2^L, .., y_{C-1}^L]^T$ can be obtained as expressed in the following equation (3).

$$\mathbf{y}^H = \left(W_{Opt}^H \right)^T \mathbf{x}^H, \quad \mathbf{y}^L = \left(W_{Opt}^L \right)^T \mathbf{x}^L \qquad (3)$$

We first construct the basic feature vector $\mathbf{Y}^{Pool} = [Y_1, .., Y_{2(C-1)}]^T = [y_1^H, y_2^H, .., y_{C-1}^H, y_1^L, y_2^L, .., y_{C-1}^L]^T$ with elements of $\mathbf{y}^H$ and $\mathbf{y}^L$. The information of discriminative power of the individual features was measured to assess the
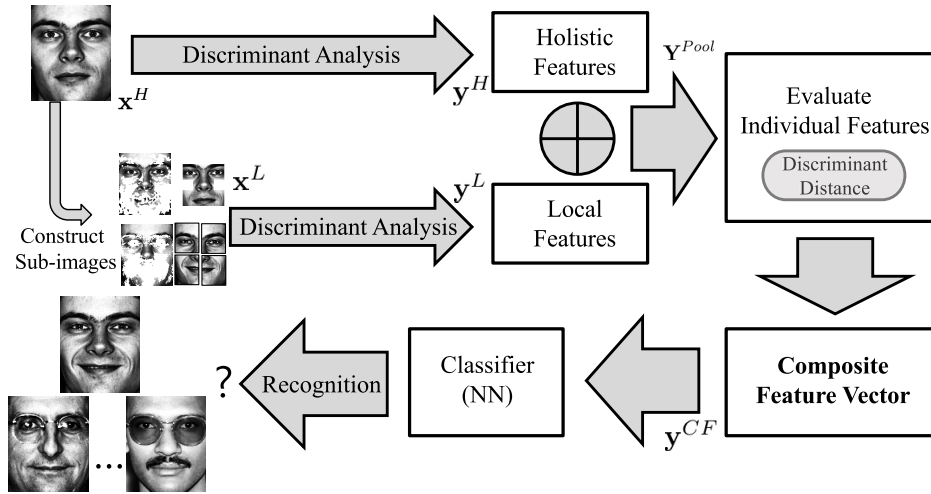
FIGURE 2. Overall procedure of face recognition using the composite feature vector.

usefulness of the basic features for face recognition. Then, based on the measurement, the composite features furnished with more discriminative powers were employed to create composite feature vectors. The discriminative power of each basic feature was measured by using the discriminant distance [33]. For Y_j, the jth component (feature) of $\mathbf{Y}^{Pool}$, the distance within a class (D_W^j), and the distance between classes (D_B^j) can be defined as expressed in the following equations (4).

$$D_W^j = \sum_{j=1}^{2(C-1)} \sum_{i=1}^{C} \frac{1}{N_i} \sum_{\mathbf{Y}^{Pool} \in c_i} \left(Y_j^i - \bar{Y}_j^i\right)^2$$

$$D_B^j = \sum_{j=1}^{2(C-1)} \sum_{i=1}^{C} \frac{N_i}{N} \left(\bar{Y}_j^i - \bar{Y}_j\right)^2 \quad (4)$$

Here, $\bar{Y}_j^i$ and $\bar{Y}_j$ denotes the jth component of mean of $\mathbf{Y}^{Pool}$s belonging to the class c_i and the jth component of mean of all $\mathbf{Y}^{Pool}$s in the training set, respectively. The discriminant distance of the jth basic feature can be defined as $D_B^j - \beta D_W^j$ from equation (4), which is used as the scale that indicates the amount of discriminative information [33]. β is the user parameter to be determined from the distribution of samples. A smaller β value that indicates the penalty of D_W^j would be favorable in the case where the within-class variance would be extended but the distribution, which would allow a comparatively favorable class discrimination. By investigating the performance for different values of β, in this paper, the value of 2 was finally determined for the β. The discriminant distance for each basic feature, $F_j = D_W^j - \beta D_B^j$, will be stored in the discriminant distance vector, $\mathbf{F} = [F_1, F_2, \ldots, F_{2(C-1)}]^T$, the size of which is equal to that of $\mathbf{Y}^{Pool}$. Based on the discriminant distance vector, the basic features corresponding to larger values of F_j will be selected to construct the composite feature vector ($\mathbf{y}^{CF}$), which is used

as inputs to the classifier for face recognition. The entire process of the proposed method is illustrated in Fig. 2.

1) The sub-image $\mathbf{x}^L$ is constructed from the given face image $\mathbf{x}^H$.
2) By using NLDA, the basic feature vector $\mathbf{Y}^{Pool}$ is constructed by extracting the holistic feature vectors ($\mathbf{y}^H$) and local feature vectors ($\mathbf{y}^L$) from $\mathbf{x}^H$ and $\mathbf{x}^L$, respectively.
3) The discriminant distance $F_j = D_W^j - \beta D_B^j$ for the basic features was then calculated.
4) The Y_j with larger values of F_j were selected to construct the composite feature vector $\mathbf{y}^{CF}$ to be used as inputs to the final classifier for face recognition.

IV. EXPERIMENTAL RESULTS
A. FACE DATABASES AND EXPERIMENTAL CONDITIONS
To show the effects of the proposed method, various face databases were taken to measure their recognition rates. The FERET database, CMU-PIE database, Yale B database, and AR database are well-known databases covering various characteristics broadly employed in face recognition studies (Table 1, Fig. 3). In order to represent the degree of variation of each database, we selected an image taken under normal conditions (no illumination and expression variations) for each subject as a reference image and computed the PSNR of the subject's other images. As shown in Table 1, the PSNR of the FERET database is higher than the other databases; thus, the images in the FERET database exhibited a relatively small variation. The FERET database contains face images of 994 subjects. Among them, two face images (fa, fb) from 992 subjects, that is, a total of 1,984 images, were used for this experiment. The two images of fa and fb can be distinguished by slight differences of varied facial expressions or of faces changed by eyeglasses, etc. Among the whole face images of the 992 subjects, those from 792 subjects that
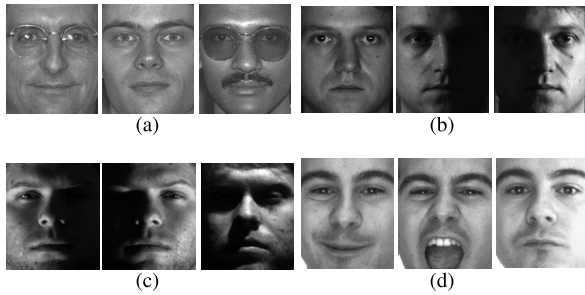
FIGURE 3. (a) FERET database, (b) CMU-PIE database, (c) Yale B database, (d) AR database. Examples from various databases.

TABLE 1. Characteristics of each database.

Database	FERET	CMU-PIE	Yale B	AR
No. of subjects	994	68	10	128
No. of images per subject	2	21	45	20
Illumination variation	none	large	large	small
Expression variation	small	none	none	large
Degree of variations (avr.PSNR)	16.9	12.6	12.4	12.1

FIGURE 4. Recognition rates of holistic features($\mathbf{y}^H$) and several kinds of local features($\mathbf{y}^L$) for various face databases.

excluded 400 images of 200 subjects, employed to make the sub-images in Section 2, were used for the evaluation of face recognition performance. Among the images, those of 100 subjects were utilized for the training images and the remaining images of 692 subjects were used as test images. For the test, the fa images were used as gallery images, whereas the images of fb were used as probe images.

The CMU-PIE database has 21 images of 68 subjects captured under different photographing conditions. In this paper, the images of 65 subjects, that is, a total of 1,365 images, were used except for the images of three subjects which were found to be defective or lacked the photographic variation under the entire 21 varied illumination conditions. For the training images, a total of 195 images that comprised the three images (27_06, 27_07, and 27_08) of slightly varied illumination for each person were used. The 27_20 images photographed under frontal illumination were used as gallery images, whereas the remaining 17 images (a total of 1,105 [= 65 × 17] images) were used as probe images.

The Yale B database also contains 45 images of varied illumination of ten subjects, where the images are categorized as Subset 1, Subset 2, Subset 3, and Subset 4 according to the degree of illumination variation. In the experiments conducted in this paper, the images of Subset 1 and Subset 2, which were taken under less varying illumination were used as gallery images and the remaining images of Subset 3 and Subset 4 were used as probe images.

The images included in the AR database were photographed from the two sessions with variations attributable to the varied illumination, facial expressions (laughing or smiling, etc.), and accessories such as sunglasses, scarves, eyeglasses, etc. Among these, images without partial occlusion were used in the experiments. The four images for
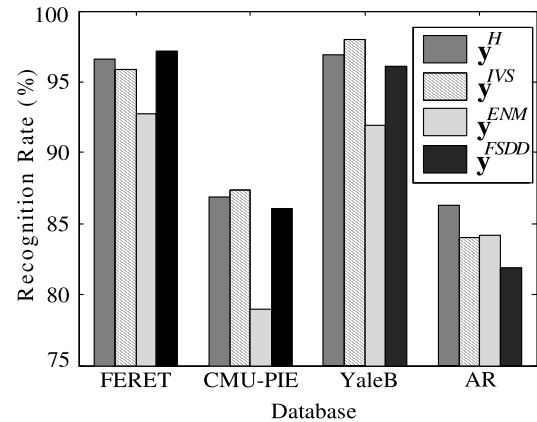
each of the 59 subjects (a total of 236 images [= 59 × 4]) were randomly selected as gallery images and training images in Session 1 whereas the seven images for each subject (a total of 413 images [= 59 × 7]) were used as probe images in Session 2. We repeated this test five times by changing the composition of the training set and reported the average recognition rates.

B. FACE RECOGNITION EVALUATION

To evaluate the performance of face recognition, the proposed composite features ($\mathbf{y}^{CF}$), the holistic features ($\mathbf{y}^H$), and the local features ($\mathbf{y}^L$, $L \in \{IVS, ENM, FSDD, SEG\}$) extracted from the whole and sub-images ($\mathbf{x}^L$, $L \in \{IVS, ENM, FSDD, SEG\}$), as well as those of the other hybrid methods ($\mathbf{y}^{CSS}$ [16], $\mathbf{y}^{Fusion}$ [17]) were compared. The NN (Nearest Neighborhood) method was employed as a classifier for face recognition and the Euclidean distance was used for the measurement of distance [4], [26]. All images were processed by histogram equalization [41] and were then normalized so that all the pixels have a zero mean value and the unit standard deviation [1], [4]. Fig. 4 shows the face recognition performance of the holistic ($\mathbf{y}^H$) and local features ($\mathbf{y}^{IVS}$, $\mathbf{y}^{ENM}$, $\mathbf{y}^{FSDD}$). In the holistic feature, the performance variance according to the database type was not large. However, in the AR database including various types of variations, the holistic feature is better than a local feature. In contrast, the local features exhibit varying effects according to the characteristics' variants present in the face images. $\mathbf{y}^{IVS}$ showed a favorable face recognition performance with the CMU-PIE database and Yale B database that contained images of varied illumination. $\mathbf{y}^{FSDD}$ showed a favorable face recognition performance from the FERET database of the face images with less varied illumination whereas it exhibited an unfavorable face recognition performance with the AR database. $\mathbf{y}^{ENM}$, extracted from the domains of the eyes, nose, and mouth of the face image, showed a relatively favorable face recognition performance from the AR database that contained the images of smiling and laughing faces. Since
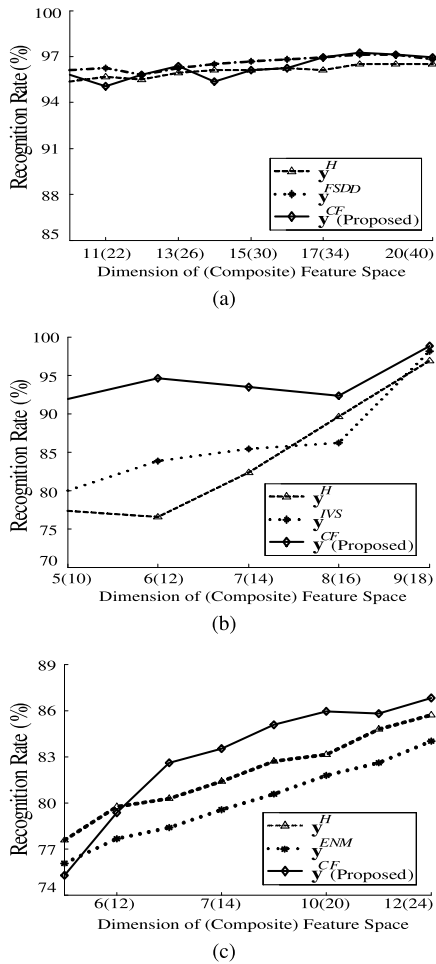
FIGURE 5. (a) FERET database, (b) Yale B database, (c) AR database. Comparison of recognition rates between the proposed method and other methods.

FIGURE 6. Comparison of recognition rates between the proposed method and other methods.

the facial muscles used when smiling are fixed, changes in the shape of the eyes, nose, and mouth according to the facial expressions can be used for face recognition training. When the recognition rate is evaluated by changing the types of variations included in the training image, we confirmed that the recognition performance was high when the images with changes of facial expressions were included in the training set. The change of the face caused by the change of illumination is strong in the eyes, nose, and mouth areas. Since the shape of the shadow due to the illumination is greatly changed around the eyes, nose, and mouth by the small change of the angle of illumination, the characteristics of the identity of the individual are weakened in the sub-images. Similarly, the holistic features or local features thus have individual advantages and disadvantages.

The performance of composite features that effectively exploited the advantages of the holistic and local features was compared to that of individual features. Fig. 5 shows the face recognition rates of the holistic, local features, and the proposed composite features from each database by increasing the dimensions of the feature space. For the comparison of local features, those that exhibited the most favorable face
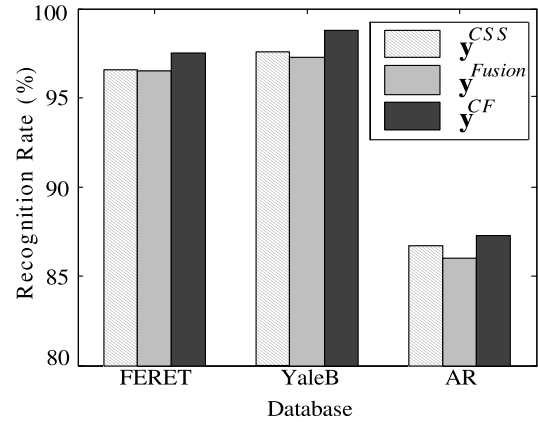
recognition performance from each database (Fig. 4) were selected, and the corresponding local features and holistic features used to construct the composite features. Regarding the FERET database where comparatively fewer varied images are contained, the performance of face recognition of holistic ($\mathbf{y}^H$) and local features ($\mathbf{y}^{FSDD}$) appeared similar to each other whereas the face recognition performance of $\mathbf{y}^{CF}$ increased from 0.3% to 0.9% compared to that of $\mathbf{y}^H$ and $\mathbf{y}^{FSDD}$. The enhancement of face recognition performance significantly increased with the composite features constructed with the desirable ones selected from the holistic and local features of the Yale B and AR databases. With the Yale B database, the face recognition rate of $\mathbf{y}^{CF}$ exceeded that of $\mathbf{y}^F$ and $\mathbf{y}^{ENM}$ by 0.8% $\sim$ 1.9% while it ranged from 1.1% to 2.8% with the AR database. Since the proposed method extracts the holistic feature and the local feature in parallel, the additional operation occurs only when evaluating the individual features (calculating discriminant distance) in the whole process of obtaining the composite features (Figure 2), which is performed almost in real time. Furthermore, the calculation of discriminant distance is performed in the only training stage, and no additional operation time occurs in the test stage.

Fig. 6 shows a comparison of face recognition performance between the proposed method and the hybrid methods that use several types of features. $\mathbf{y}^{CSS}$ indicates the features that simply combined the holistic and local features of the eyes, nose, and mouth [16] and $\mathbf{y}^{Fusion}$ denotes the fusion rule for the use of holistic and local features together [17]. Fig. 6 shows that the proposed composite features that select only good features by discriminant analysis show a better recognition performance than other hybrid methods for all databases.

V. CONCLUSION

The holistic features extracted from the whole image of a face and the local features extracted from its sub-images have different characteristics in face recognition. In this paper, a method to construct composite features by selecting features equipped with rich information for face recognition

from the holistic and local features was presented. For this purpose, the holistic and local features were extracted from the whole and sub-images of a face by using NLDA. Then, the amount of discriminative information contained in each extracted feature was measured by discriminant analysis and the composite features consisting of features rich in discriminative information were employed for face recognition. The face recognition performance was evaluated with images obtained from the FERET database, CMU-PIE database, Yale B database, and AR database. The proposed method exhibited superior face recognition performance compared to using only the holistic or local features. The method also showed a comparatively higher face recognition performance than other methods, including hybrid methods. It is therefore expected that the method for the construction of composite features presented in this paper can be combined with other extraction methods to improve the discipline of pattern recognition performance as well as that of face recognition.

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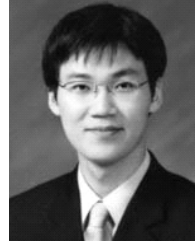
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