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Face Recognition Using Local and Global Features

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The combining classifier approach has proved to be a proper way for improving recognition performance in the last two decades. This paper proposes to combine local and global facial features for face recognition. In particular, this paper addresses three issues in combining classifiers, namely, the normalization of the classifier output, selection of classifier(s) for recognition, and the weighting of each classifier. For the first issue, as the scales of each classifier's output are different, this paper proposes two methods, namely, linear-exponential normalization method and distribution-weighted Gaussian normalization method, in normalizing the outputs. Second, although combining different classifiers can improve the performance, we found that some classifiers are redundant and may even degrade the recognition performance. Along this direction, we develop a simple but effective algorithm for classifiers selection. Finally, the existing methods assume that each classifier is equally weighted. This paper suggests a weighted combination of classifiers based on Kittler's combining classifier framework. Four popular face recognition methods, namely, eigenface, spectroface, independent component analysis (ICA), and Gabor jet are selected for combination and three popular face databases, namely, Yale database, Olivetti Research Laboratory (ORL) database, and the FERET database, are selected for evaluation. The experimental results show that the proposed method has 5–7% accuracy improvement.

Keywords and phrases: local and global features, face recognition, combining classifier.

1. INTRODUCTION

Face recognition research started in the late 70s and has become one of the active and exciting research areas in computer science and information technology areas since 1990. Basically, there are two major approaches in automatic recognition of faces by computer [1, 2], namely, constituent-based recognition (we called as local feature approach) and face-based recognition (we called as global feature approach).

A number of face recognition algorithms/systems have been developed in the last decade. The common approach is to develop a single, sophisticated, and complex algorithm to handle one or more face variations. However, developing a single algorithm to handle all variations (including pose variation, luminance variation, light noise, etc.) is not easy. It is known that different classifiers have their own characters to handle different facial variations and certain classifiers may be only suitable for one specific pattern. Moreover, the misclassified samples may not be overlapped. Therefore, combining different classifiers' output to draw a final conclusion can improve the performance.

Ackermann and Bunke [3] combined two full-face (global) classifiers, namely, HMM, eigenface, and a profile classifier for face recognition in 1996. They proposed different schemes for combining classifiers. Encouraging results have been shown. As their testing images mainly are captured under well-controlled lighting environment and the individual method has achieved good results, the improvement using combining classifiers was not significant.

Kittler et al. [4] developed a theoretical framework for

combining classifiers in 1998. They developed a nice theoretical framework and suggested four combination rules. They also applied the rules in combining face, voice, and fingerprint recognition for person authentication. The results are encouraging. Moreover, they pointed out that sum rule, in general, gives a relatively good result.

Tax et al. [5] further discussed the topic of combining multiple classifiers by averaging or by multiplying. They pointed out that averaging-estimated posterior probabilities would give good performance when posterior probabilities are not well estimated. However, averaging rule does not have solid Bayesian foundation.

This paper proposes to make use of both local features and global features for face recognition. Many face recognition algorithms have been developed and we have selected four current and popular methods, namely, eigenface [6, 7, 8], spectroface [9], independent component analysis (ICA) [10, 11, 12, 13, 14], and Gabor jet [15, 16] for combination. The preliminary version of this paper has been reported in [17]. The contributions of this paper are mainly on how to combine these methods to draw the final conclusion and are summarized as follows:

(i) two normalization methods for combining each classifier's output;
(ii) a simple but efficient algorithm for selecting classifiers;
(iii) a weighted combination rule.

The organization of this paper is as follows. Section 2 gives a brief review on Kittler's combining classifier theory [4] and the four face recognition methods. Section 3 presents our proposed normalization methods. Our proposed classifier selection algorithm and weighted combination rule are reported in Section 4. Section 5 gives the experimental results. Conclusion is given in Section 6.

2. A BRIEF REVIEW ON EXISTING METHODS

This section is divided into two parts. The first part outlines the classifier combination theory developed by Kittler et al. [4]. The second part reviews the four face recognition methods, namely, eigenface, spectroface, ICA, and Gabor jet that we are going to use for classifier combination.

2.1. Review on combination theoretical framework

Consider a face image Z to be assigned to one of the m possible classes $(\omega_1, \omega_2, \ldots, \omega_m)$ and let x_i be the measurement vector to be used by the ith classifier. So, in the measurement space, each class ω_k is modeled by the probability density function $p(x_i|\omega_k)$, and its prior probability of occurrence is denoted by $p(\omega_k)$. The joint probability distribution of the measurement extracted by the classifiers is $p(x_1, x_2, \ldots, x_R|\omega_k)$, where R is the number of features to be used for classification. A brief description of classifier combination schemes and strategies [4] is as follows.

Classifier combination scheme: product rule

The product rule quantifies the likelihood of a hypothesis by combining the a posteriori probability generated by each individual classifier and is given as follows:

$$\text{assign } Z \longrightarrow \omega_{k^0} \quad \text{if } k^0 = \arg\max_k \left[P^{-(R-1)}(\omega_k) \prod_{i=1}^{R} P(\omega_k|x_i) \right]. \tag{1}$$

Classifier combination scheme: sum rule

In the product rule, if we assume that the a posteriori probability computed by the respective classifiers will not deviate dramatically from the a priori probability, the sum rule can be obtained as follows:

$$\text{assign } Z \longrightarrow \omega_{k^0} \quad \text{if } k^0 = \arg\max_k \left[(1-R)P(\omega_k) + \sum_{i=1}^{R} P(\omega_k|x_i) \right]. \tag{2}$$

Classifier combination scheme: max rule

In the sum rule, if we approximate the sum by the maximum of the a posteriori probabilities and assume equal a priori ones, we get the following:

$$\text{assign } Z \longrightarrow \omega_{k^0} \quad \text{if } k^0(i^0) = \arg\max_k \left(\arg\max_i P(\omega_k|x_i) \right). \tag{3}$$

Classifier combination strategy: min rule

From the product rule, by bounding the product of the a posteriori probabilities and under the assumption of equal a priori ones, we get the following:

$$\text{assign } Z \longrightarrow \omega_{k^0} \quad \text{if } k^0(i^0) = \arg\max_k \left(\arg\min_i P(\omega_k|x_i) \right). \tag{4}$$

2.2. Review on face recognition methods

This paper proposes to make use of both local features and global features for face recognition, and performs experiments in combining two global feature face recognition algorithms, namely, principal component analysis (PCA), spectroface, and two local feature algorithms, namely, Gabor wavelet and ICAs. The brief descriptions on each method are as follows.

2.2.1. Principle component analysis (eigenface)

This idea of using the PCA for face recognition [6, 8] was first proposed by Sirovich and Kirby [7]. Consider face images of size $k \times k$. Let $X = \{X_n \in R^d \mid n = 1, \ldots, N\}$ be an ensemble of row vectors of training face images. Then X corresponds to a $d \times N$-dimensional face space. PCA tries to find a lower dimensional subspace to describe the original face space. Let

$$E(X) = \frac{1}{N} \sum_{n=1}^{N} X_n \tag{5}$$

be the average vector of the training face image data in the ensemble. After subtracting the average face vector from each

face vector X, we get a modified ensemble of vectors,

$$\overline{X} = \{\overline{X}_n,\ n = 1,\ldots,N\}, \quad \overline{X}_n = X_n - E(X). \tag{6}$$

The autocovariance matrix M for the ensemble $\overline{X}$ is defined as follows:

$$M = \operatorname{cov}(\overline{X}) = E(\overline{X} \cdot \overline{X}), \tag{7}$$

where M is a $d \times d$ matrix. The eigenvectors of the matrix M form an orthonormal basis for R^d. Now the PCA of a face vector y related to the ensemble X is obtained by projecting vector y onto the subspace spanned by k eigenvectors corresponding to the top k eigenvalues of the autocorrelation matrix M in descending order, where k is smaller than N. This projection results in a vector containing k coefficients $a_1,\ldots,a_k$. The vector y is then represented by a linear combination of the eigenvectors with weights $a_1,\ldots,a_k$.

2.2.2. Spectroface

Spectroface method [9] combined the wavelet transform and the Fourier transform for feature extraction. Wavelet transform is first applied to the face image in order to eliminate the effect of different facial expression and reduce the resolution of the image. Then we extract the holistic Fourier invariant features (HFIF) from the low-frequency subband image. There are two types of spectroface representations, namely, the first-order spectroface and the second-order spectroface. The first-order spectroface extracts features, which are translation invariant and insensitive to the facial expressions, small occlusion, and minor pose changes. The second-order spectroface extracts features that are translation, on-the-plane rotation, and scale invariant, and insensitive to the facial expressions, small occlusion, and minor pose changes. The second-order spectroface is outlined as follows. Applying the Fourier transform on a certain low-frequency subband image $f(x, y)$, its spectrum is given by $F(u, v)$. By flipping the DC component (the term with zero frequency) that is the upper-left corner of the two-dimensional fast Fourier transform (FFT) to the center of the spectrum, we can find a natural center for polar coordinate. Hence the spectrum $F(u, v)$ can be rewritten in polar form as $F(\rho, \varphi)$. In [9], a moment transform is defined as follows:

$$C_{nm} = \frac{1}{2\pi L} \int_0^{2\pi} \int_{R_0}^{R_1} F(\rho,\varphi) e^{-i((2\pi n/L)\ln\rho + m\varphi)} \frac{1}{\rho} d\rho\, d\varphi. \tag{8}$$

The amplitude values $|C_{nm}|$ have been proved to be invariant to translation, scale, and on-the-plane rotation [9]. Hence we can extract the second-order spectroface feature matrix $C = [|C_{nm}|]$ that is invariant to translation, on-the-plane rotation, and scale, and insensitive to the facial expressions, small occlusions, and minor pose changes.

2.2.3. Independent component analysis

ICA is a statistical signal processing technique. The concept of ICA can be seen as a generalization of the PCA, which only impose independence up to the second order. The basic idea of ICA is to represent a set of random variables using basis functions, where the components are statistically independent or as independent as possible (as it is only an approximated solution in practice) [10, 11, 12, 13, 14, 16]. We classified ICA as a local feature technique because the ICA basis represents image locally.

Here, the density of probability defines the so-called independence. Two random variables are statistically independent if and only if the joint probability density is *factorizable*, namely, $p(y_1, y_2) = p_1(y_1)p_2(y_2)$. Given two functions h_1 and h_2, the most important property of independent random variables is defined as follows:

$$E\{h_1(y_1)h_2(y_2)\} = E\{h_1(y_1)\}E\{h_2(y_{21})\}. \tag{9}$$

A weaker form of independence is uncorrelated. Two random variables are said to be uncorrelated if their covariance is zero:

$$E\{y_1 y_2\} = E\{y_1\}E\{y_2\}. \tag{10}$$

So independence implies uncorrelation, but uncorrelated variables are only partly independent. For simplifying the problem and reducing the number of free parameters, many ICA methods constrain the estimation procedure so that it always gives uncorrelated estimates of the independent components [14].

Applying the ICA on face recognition, the random variables will be the training face images. Letting x_i be a face image, we can construct a training image set $\{x_1, x_2, \ldots, x_m\}$ which are assumed to be linear combinations of n independent components $s_1, s_2, \ldots, s_n$. The independent components are mutually statistically independent and with zero-mean. We denote the observed variables x_i as an observed vector $X = (x_1, x_2, \ldots, x_m)^T$ and the component variables s_i as a vector $S = (s_1, s_2, \ldots, s_m)^T$. The relation between S and X can be modeled as $X = AS$, where A is an unknown $m \times n$ matrix of full rank, called the mixing/feature matrix. The columns of A represent features, and s_i signals the amplitude of the ith feature in the observed data x. If the independent components s_i have a unit variance, that is, $E\{s_i s_i\} = 1$, $i = 1, 2, \ldots, n$, it will make independent components unique, except for their signs.

2.2.4. Local Gabor wavelet (Gabor jet)

Since Daugman applied Gabor wavelet on iris recognition in 1988 [16], Gabor wavelet has been widely adopted in the field of object and face recognition. Wiskott et al. [15] developed a system for face recognition using elastic bunch graph matching using Gabor wavelet.

This paper selects 23 points (instead of 48), as shown in Figure 1, for recognition. These points lie at the corner or nonsmooth positions of important landmarks on face images as these locations contain more information than other points in smooth regions. All landmarks are selected manually.

Giving one face image $I(\vec{x})$, we can apply a Gabor wavelet transform to get a jet on each pixel $\vec{x} = (x, y)$. The Gabor

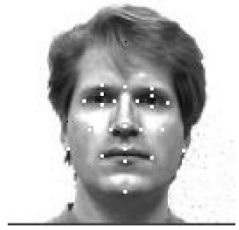

Figure 1: Twenty-three points are marked manually on the face image.

wavelet response is defined as a convolution of the object image with a family of Gabor kernels with different orientations and scales:

$$\Im_j(\vec{x}) = \int I(\vec{x'})\varphi_j(\vec{x}-\vec{x'})d^2\vec{x'} \tag{11}$$

with the Gabor kernels as follows:

$$\varphi_j(\vec{x}) = \frac{k_j^2}{\sigma^2}\exp\left(-\frac{k_j^2x^2}{2\sigma^2}\right)\left[\exp\left(i\vec{k_j}\vec{x}\right)-\exp\left(-\frac{\sigma^2}{2}\right)\right]. \tag{12}$$

The Gabor kernels are given by the shapes of plane waves with wave vector $\vec{k}_j$ restricted by a Gaussian envelope function. We perform the transformation by 5 different frequencies and 8 orientations. So we get 40 Gabor wavelet coefficients $\{\Im_j = a_j\exp(i\phi_j),\ j = 1,\ldots,40\}$ for one jet $\Im$. Then the comparison between two face images becomes the comparisons of jets on the two images. The similarity between two jets is given as follows:

$$\begin{aligned} S_a(\Im,\Im') &= \frac{\sum_j a_j a'_j}{\sqrt{\sum_j a_j^2 a_j'^2}}, \\ S_\phi(\Im,\Im') &= \frac{\sum_j a_j a'_j\cos\left(\phi_j-\phi'_j-\vec{d}\vec{k}_j\right)}{\sqrt{\sum_j a_j^2 a_j'^2}}, \end{aligned} \tag{13}$$

where $\vec{d}$ is a relatively small displacement between two jets $\Im$ and $\Im'$.

3. PROPOSED NORMALIZATION METHODS

We have reviewed four popular facial feature extraction methods, and outputs of each method are in different scales. Spectroface, PCA, and ICA use distance measurement for classification, while local Gabor wavelet use similarity measurement. To combine the four methods, the distance measurement and the similarity measurement from the outputs of different classifiers should be normalized at the same scale. Transformation is proposed to solve the problem. The transformation must not affect the order of the ranking of the transformed data. So these transforms should be monotone functions. We propose two normalization methods, namely, linear-exponential normalization method (LENM) and distribution-weighted gaussian normalization method (DWGNM). The LENM is developed based on traditional normalization method, which will be discussed in Section 3.1. The DWGNM is developed based on the concept of normal distribution. The experimental results (in Section 5) show that both normalization methods give very good results.

3.1. Two basic transforms for scale normalization

Suppose the original data are in the range of DataIn $= [\alpha_1,\alpha_2]$, and we want to convert them to the range of DataOut $= [\beta_1,\beta_2]$. Ackermann and Bunke [3] proposed the following two normalization transformations, namely, linear transformation and logistic transformation. The linear transformation is by:

$$\text{DataOut} = \beta_1 + \frac{(\text{DataIn}-\alpha_1)}{(\alpha_2-\alpha_1)} * (\beta_2-\beta_1). \tag{14}$$

A logistic transformation can be performed with the following steps. First, use the linear transformation in (14) to convert the input data into scope $S = [0.0, 100.0]$. Then the logistic transformation is given as follows:

$$S^{\log} = \frac{\exp(\alpha+\beta S)}{1+\exp(\alpha+\beta S)}. \tag{15}$$

Generally, the parameters $\alpha > 0$ and $\beta > 0$, which control the intersection with the X-axis and slope, respectively, can be determined empirically.

To solve the combining problem, we propose to convert the distance measurement to similarity measurement (or estimated probability) with scale normalization. But the two above-mentioned transformations cannot be used as a normalization method directly in the data fusion process because the input data consists of both distance measurement and similarity measurement and they are inversely related. So we propose LENM based on the logistic transformation. Then we propose DWGNM based on the properties of normal distribution function.

We denote the distance between pattern Z_i and the training sample Z_j with d_{ij}, S_{ij} is the similarity between them, and p_{ij} is the estimated probability that pattern Z_i belongs to the class of training sample Z_j. We denote σ as follows:

$$\sigma = \sqrt{\frac{\sum_{i,j} d_{ij}^2}{N}}, \tag{16}$$

where N is the total number of the distances.

3.2. Linear-exponential normalization method

The LENM consists of two steps. First, we use the linear transformation to convert the input data $d_{ij} \in [\alpha_1,\alpha_2]$ into output data scope $[\beta_1 = 0.0,\ \beta_2 = 10.0]$. From (14), we can get

$$d'_{ij} = \frac{d_{ij}-\alpha_1}{\alpha_2-\alpha_1} * 10. \tag{17}$$

Then, substituting (17) into (15), we get

$$d''_{ij} = \frac{\exp(\alpha + \beta d'_{ij})}{1 + \exp(\alpha + \beta d'_{ij})}. \quad (18)$$

As we know that the similarity between two patterns is inversely proportional to the distance between them. So an inverse relationship can be denoted as the following:

$$\text{Similarity} = k\frac{1}{\text{distance}}. \quad (19)$$

Substituting (18) into (19), and let $k = 1$, we get:

$$S_{ij} = \frac{1 + \exp(\alpha + \beta d''_{ij})}{\exp(\alpha + \beta d''_{ij})}. \quad (20)$$

It can be seen that S_{ij} is inversely related to d_{ij}. But if the value of $\exp(\alpha + \beta d''_{ij})$ is large, all S_{ij} will give the same value for most of the values of α, β. In our experiments, we found that it is difficult to estimate the appropriate values of α, β if we do not know the exact scale of each classifier output. Therefore, we further modify this method as follows.

First, we convert d_{ij} into scope $[0.0, 10.0]$ just as in (17), then substituting (17) into (16), we get

$$\sigma' = \sqrt{\frac{\sum_{i,j} d'^2_{ij}}{N}}. \quad (21)$$

Second, we compute the similarity as follows:

$$S^1_{ij} = \frac{\exp(\sigma')}{\exp(\sigma') + \exp(\alpha + \beta d'_{ij})}. \quad (22)$$

Here we convert d_{ij} into the scope $[0.0, 10.0]$ because we do not want the exponential term $\exp(\sigma')$ to be too large. In this way, the parameters α, β can be estimated easily.

We can also normalize the similarity measurement to estimated probability measurement. This is done in the following manner. Using the linear transformation in (14) to convert $S^1_{ij} \in [S_1, S_2]$ into scope $[0.0, 1.0]$, we have

$$p^1_{ij} = \frac{S^1_{ij} - S_1}{S_2 - S_1}. \quad (23)$$

3.3. Distribution-weighted Gaussian normalization method

The linear-exponential normalization is developed based on the logistic transformation. Though the determination of α, β is not a problem, but we still need to determine the parameters. Therefore, we design another method from the distribution density function perspective [18]. We know that the distribution of a large number of random data will obey the normal distribution. So we propose the DWGNM based on the concept of the normal distribution. Along this direction, we propose to employ the normal distribution as shown in Figure 2, as a weighting factor of the normalization.

The normal distribution function with mean μ and variance σ^2 is given as follows:

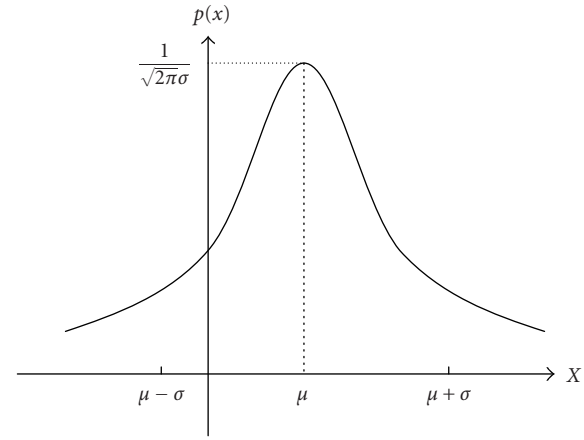

Figure 2: The normal distribution.

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(X-\mu)^2/2\sigma^2}, \quad -\infty < x < +\infty. \quad (24)$$

Figure 2 shows that the closer the point is to μ, the larger $p(x)$ will be. The rate of declination is controlled by σ. In employing the normal distribution, we have the following modifications:

(i) only the positive side is used, as distance is always positive;

(ii) the peak of the distribution is normalized from $1/(\sqrt{2\pi}\sigma)$ to 1;

(iii) the mean is shifted to zero, that is, $\mu = 0$.

Then we can compute the similarity as follows:

$$S^2_{ij} = \exp\left(-\frac{d^2_{ij}}{2\sigma^2}\right), \quad (25)$$

where σ is defined as (16). As $d^2_{ij}/\sigma^2 \geq 0$, so $0 < S^2_{ij} \leq 1$, and S^2_{ij} is inversely related to d_{ij}.

Again, we can also convert the similarity measurement to estimated probability measurement. If $S^2_{ij} \in [S^2_1, S^2_2]$, using (14), we have

$$p^2_{ij} = \frac{S^2_{ij} - S^2_1}{S^2_2 - S^2_1}. \quad (26)$$

4. PROPOSED CLASSIFIER SELECTION ALGORITHM AND WEIGHTED COMBINATION RULE

This section is divided into two parts. The first part reports the proposed classifier selection algorithm. The second part reports the proposed weighted combination rule.

4.1. Classifier selection algorithm

A number of research works have demonstrated that the use of multiple classifiers can improve the performance [18, 19]. However, is it the more the classifiers, the better the results

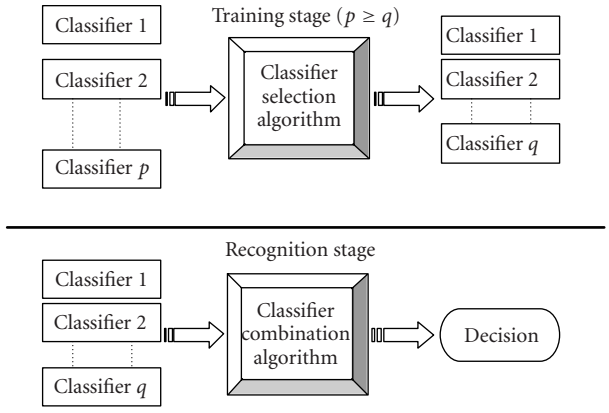

Figure 3: Pattern recognition system with classifier selection.

will be? From our experience, some classifiers are redundant. In the worst case, the redundant classifiers may degrade the performance. Therefore, in this section, we design and develop a simple but efficient classifier selection algorithm to select the best set of classifiers for recognition.

It is well known that a pattern recognition system consists of two stages, namely, training stage and recognition stage. The proposed classifier selection algorithm is performed at the training stage as shown in Figure 3. Suppose there is a set of p input classifiers; our classifier selection algorithm removes the redundant classifiers and eventually selects q ($q \leq p$) classifiers to be employed in the recognition stage. The detailed classifier selection algorithm is presented below.

The proposed method is based on the leave-one-out algorithm and is an iterative scheme. Assume that the combining classifier scheme is fixed. The basic idea of the scheme is that if one classifier is redundant, the accuracy will increase if that classifier is removed from combination. Based on this idea, the following algorithm is proposed.

Suppose we have p classifiers to be combined, denoted by a set of classifiers $C_0 = \{c_j,\ j = 1, 2, \ldots, p\}$. Let O_a be the accuracy obtained when all classifiers are used for combination and $A_k = \{a_i^k,\ i = 1, 2, \ldots, p\}$ be the accuracy obtained at the kth iteration, where a_i^k represents the accuracy obtained when the classifier c_i is removed. The set of classifiers after kth iteration is denoted by $C_k = \{c_j,\ j = 1, 2, \ldots, p$ and $c_j \notin$ RC$\}$, where RC is the set that contains all redundant classifiers (RC is a null set at the beginning).

In the first iteration, we take one of the classifiers out and the rest are used for combination. We will obtain a set of accuracy $A_1 = \{a_i^1,\ i = 1, 2, \ldots, p\}$. The highest accuracy HA_1 is determined, where $HA_1 = a_{i_1}^1 = \max_i\{a_i^1\}$. If $HA_1 \geq O_a$, then the classifier c_{i_0} will be removed from C_0 and inserted in RC. A new set of classifiers C_1 is obtained, where $C_1 = \{c_j,\ j = 1, 2, \ldots, p$ and $c_j \notin$ RC$\}$ and RC is updated from null set to $\{c_{i_1}\}$. Otherwise, all classifiers should be kept for combination and the iteration stops.

If the classifier is removed in the previous iteration, another iteration is required. To present a general case, suppose that the kth iteration is required. In the $(k-1)$th iteration, we get $C_{k-1} = \{c_j,\ j = 1, 2, \ldots, p$ and $c_j \notin$ RC$\}$ and RC is updated as well. Again, we take one of the classifiers out from C_{k-1} and determine a set of accuracies by combining the rest of classifiers. A set of accuracies is then obtained $A_k = \{a_i^k,\ i = 1, 2, \ldots, p\}$ (assign a negative value to a_q^k if $c_q \in$ RC). The highest accuracy $HA_k = a_{i_k}^k = \max_i\{a_i^k\}$ is determined from A_k. If $HA_k \geq HA_{k-1}$, remove the c_{i_k} from C_{k-1} and insert into RC. A new set of C_k is constructed and RC is updated. Another iteration is then proceeded. If $HA_k < HA_{k-1}$, the iteration will stop. The set C_{k-1}, containing the rest of classifiers, will be used for combination.

We will demonstrate the proposed algorithm using the FERET database in Section 5.4.

4.2. Weighted combination rule

Kittler et al. [4] presented a nice and systematic theory framework for combining classifiers. The performance on their framework is very encouraging. This paper will make some modifications based on the sum rule in their framework. As we know, Kittler et al.'s theory framework considered all classifiers equally, that is, contributions to each classifier to the final decision are equal. This paper proposes to weight each classifier with a confidence function to represent the degree of contributions. As the recognition accuracy of each classifier is directly related to the confident, we can generate confidence function as a weighting function. Here, again the recognition accuracy a priori information is acquired at the training stage.

Let r_i be the recognition accuracy of each classifier and the sum of the recognition accuracy $r = \sum_{j=1}^{q} r_j$, where q is the number of classifiers you want to combine. In our case, we assume that a priori probability of each class is equal. That is,

$$P(\omega_j) = P(\omega_k), \quad k \neq j. \tag{27}$$

So we can simplify the sum rule (2) as follows:

$$\begin{aligned} &\text{assign } Z \longrightarrow \omega_{k^0} \\ &\text{if } k^0 = \arg\max_k \left[\sum_{i=1}^{q} P(\omega_k | x_i) \right]. \end{aligned} \tag{28}$$

Then we can get the weighted combination rule based on expression (2) as follows:

$$\begin{aligned} &\text{assign } Z \longrightarrow \omega_{k^0} \\ &\text{if } k^0 = \arg\max_k \left[\sum_{i=1}^{q} \frac{r_i}{r} P(\omega_k | x_i) \right]. \end{aligned} \tag{29}$$

Here, r_i/r is the weighting function that satisfies

$$\sum_{i=1}^{q} \frac{r_i}{r} = 1. \tag{30}$$

5. EXPERIMENTAL RESULTS

Four experimental results are presented in this section to demonstrate the performance of the proposed algorithms. Section 5.2 will report the results on the normalization

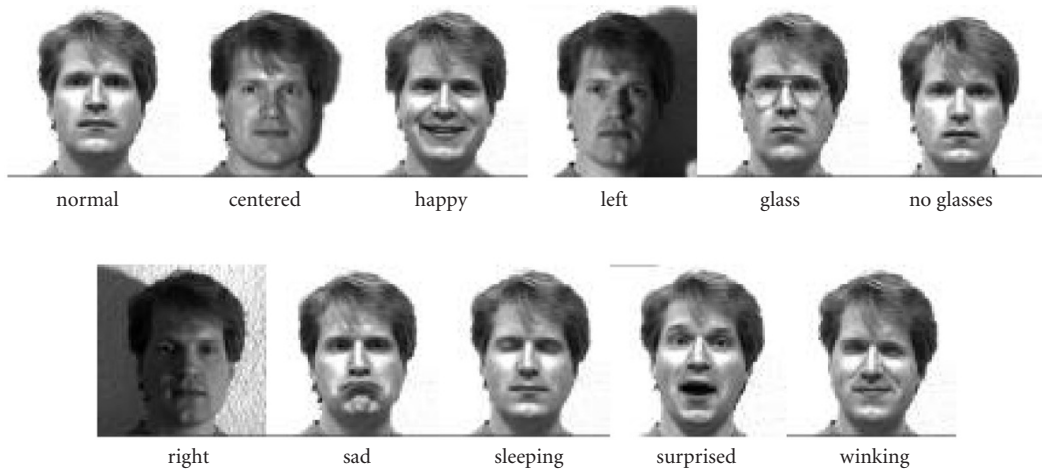

Figure 4: Images of one person from Yale database.

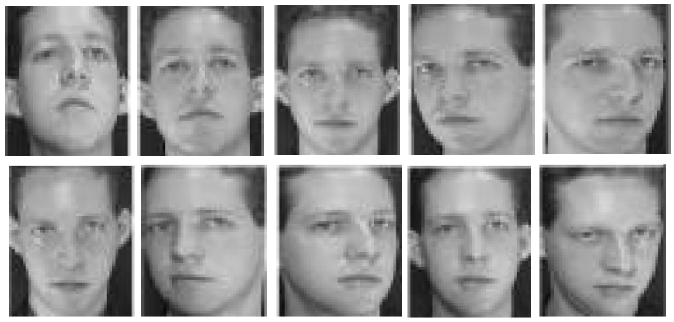

Figure 5: Images of one person from Olivetti database.

Figure 6: Images of one person from the FERET database.

methods using the four combination rules. The results on the proposed weighted combination rule are given in Section 5.3. Section 5.4 illustrates the steps in the proposed classifier selection algorithm to find the best set of classifiers for recognition. The result shows that the eigenface (PCA) method is redundant with the other methods and can be removed. Finally, Section 5.5 reports a microscopic analysis on why combining global and local features can improve the performance. Before describing the detailed experimental results, let's discuss the testing face databases in Section 5.1

5.1. Databases

Three public available face databases, namely, Yale face database, Olivetti research laboratory (ORL) face database, and FERET database are selected to evaluate the performance of the proposed method.

In Yale database, there are 15 persons and each person consists of 11 images with different facial expressions, illumination, and small occlusion (by glasses). And the resolution of all images is 128×128. Image variations of one person in the database are shown in Figure 4.

In Olivetti database, there are 40 persons and each person consists of 10 images with different facial expressions, small scale, and small rotation. Image variations of one person in the database are shown in Figure 5.

FERET database consists of 70 people, 6 images for each individual. The 6 images are extracted from 4 different sets, namely, Fa, Fb, Fc, and duplicate [20]. Fa and Fb are sets of images taken with the same camera at the same day but with different facial expressions. Fc is a set of images taken with different camera at the same day. Duplicate is a set of images taken around 6–12 months after the day of taking the Fa and Fb photos. All images are aligned by the centers of eyes and mouth and then normalized with resolution 92×112. Images from one individual are shown in Figure 6.

Table 1: Results on original Yale database.

Method	Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Spectroface	90.8333	94.1667	96.6667
PCA	72.5000	80.0000	81.6667
ICA	70.8333	79.1667	84.1667
Local Gabor wavelet	87.5000	95.0000	96.6667

Table 2: Results of LENM on Yale database.

Scheme		Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Similarity measurement (22)	Product rule	92.5000	97.5000	99.1667
	Sum rule	93.3333	97.5000	100.000
	Min rule	76.6667	86.6667	88.3333
	Max rule	91.6667	95.0000	95.0000
Estimated probability measurement (23)	Product rule	89.1667	96.6667	97.5000
	Sum rule	92.5000	97.5000	99.1667
	Min rule	83.3333	87.5000	91.6667
	Max rule	91.6667	96.6667	97.5000

Table 3: Results of DWGNM on Yale database.

Scheme		Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Similarity measurement (25)	Product rule	93.3333	97.5000	100.000
	Sum rule	94.1667	97.5000	100.000
	Min rule	76.6667	86.6667	88.3333
	Max rule	93.3333	96.6667	97.5000
Estimated probability measurement (26)	Product rule	92.5000	95.8333	98.3333
	Sum rule	94.1667	97.5000	100.000
	Min rule	81.6667	86.6667	90.0000
	Max rule	91.6667	95.8333	97.5000

Table 4: Results on Olivetti database.

Method	Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Spectroface	77.8571	81.7857	86.4286
PCA	70.3571	78.9286	82.8571
ICA	72.8571	81.7857	85.0000
Local Gabor wavelet	53.9286	60.7143	66.0714

Table 5: Results of LENM on Olivetti database.

Scheme		Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Similarity measurement (22)	Product rule	83.5714	88.9286	90.7143
	Sum rule	85.0000	89.2857	91.0714
	Min rule	62.1429	73.5714	80.3571
	Max rule	84.2857	89.6429	91.4286
Estimated probability measurement (23)	Product rule	83.9286	88.2143	90.3571
	Sum rule	84.6429	89.2857	91.0714
	Min rule	76.7857	82.5000	87.8571
	Max rule	62.5000	70.3571	75.0000

Table 6: Results of DWGNM on Olivetti database.

Scheme		Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Similarity measurement (25)	Product rule	82.5000	88.5714	90.7143
	Sum rule	83.2143	88.9286	90.7143
	Min rule	71.4286	76.4286	80.7143
	Max rule	81.7857	87.5000	89.2857
Estimated probability measurement (26)	Product rule	83.5714	88.9286	91.0714
	Sum rule	84.6429	88.5714	91.0714
	Min rule	77.1429	82.1429	87.1429
	Max rule	67.5000	74.2857	80.3571

As the number of individuals in Yale and ORL databases is relatively small, we will make use of the FERET database for evaluating the proposed classifier selection algorithm in Section 5.4. Moreover, we would like to highlight that the objective of this paper is to demonstrate the advantages and efficiency of combining local and global features for face recognition. The following experiments will demonstrate the improvement of combining global and local features over each individual method. The accuracy can be further increased if more or different training images are used.

5.2. Results of proposed normalization methods

5.2.1. Results on Yale database

In this experiment, only the normal images are used for training and all other images are used for testing. Table 1 shows the rank 1 to rank 3 results (rank(n) is considered as a correct match if the target image is located at the top n images on the list). The rank 1 accuracies for these four methods are ranging from 70.8% to 90.8%. Please note that the performance is not as good as that stated in the original article because of two reasons:

(i) only one face image is used for training,

(ii) the two poor lighting images (left and right images) are also used for testing.

Now we see the results on combining classifiers. Same experiment settings but different normalization methods are used. For each normalization method, all four combination schemes are used to evaluate the performance of each combination. Again, rank 1 to rank 3 accuracies are recorded. The results of LENM and DWGNM are tabulated in Tables 2 and 3, respectively.

Results of LENM in Table 2 shows that among the four rules, sum rule provides the best result based on either similarity or estimated probability. The rank 1 accuracy is 93.33% while the rank 3 accuracy is 100.00%. Comparing with best performance in Table 1, which is spectroface, there is around 2.5% improvement.

Results of DWGNM are better than these of LENM. As shown in Table 3, the result of DWGNM with sum rule is 94.17%, which is around 0.8% higher than that of LENM.

5.2.2. Results on Olivetti database

Similar experiments are performed using Olivetti database. The first frontal-view image for every person is used for training, while the rest of the 7 images are used for testing. Table 4 shows the results on Olivetti database. The rank 1 accuracy is ranging from 53.93% to 77.86%.

Now we look at the results on combining classifiers. Tables 5 and 6 show the results of LENM and DGWNM. Again

Table 7: Results of DGWNM on Yale database.

Scheme		Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Similarity measurement (25)	Sum rule	94.1667	97.5000	100.000
	Weighted combination rule	95.0000	97.5000	100.000
Estimated probability measurement (26)	Sum rule	94.1667	97.5000	100.000
	Weighted combination rule	95.0000	97.5000	100.000

Table 8: Results of DGWNM on Olivetti database.

Scheme		Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Similarity measurement (25)	Sum rule	83.2143	88.9286	90.7143
	Weighted combination rule	84.2857	89.2857	90.7143
Estimated probability measurement (26)	Sum rule	84.6429	88.5714	91.0714
	Weighted combination rule	85.0000	89.2857	90.7143

the four rules are evaluated and rank 1 to rank 3 accuracies are recorded. It can be seen that the sum rule gives the best performance among the four rules. The highest rank 1 accuracy reaches 85.0%. Comparing with the best performance for individual method, 7.2% improvement is obtained.

5.3. Results of proposed weighted combination rule

In the above section, we have seen the performance of two proposed normalization methods on two popular face databases. Now we will compare the performance of the sum rule, which gives the best performance in Kittler et al. combination theory, with our proposed weighted combination rule using DWGNM.

5.3.1. Results on Yale database

The experiments are the same as before, except the weighted combination rule is added for comparison. The results are shown in Table 7. It can be seen that for both similarity measurement (based on (25)) and estimated probability measurement (based on (26)), the proposed weighted combination rule performs better than the sum rule by 0.8%.

5.3.2. Olivetti database

The results on ORL database are shown in Table 8. It can be seen that the weighted combination rule gives a better performance than that of sum rule by 0.4–1%.

5.4. Results of classifier selection algorithm

The detailed classifier selection algorithm has been reported in Section 4.1. This section demonstrates its performance. As mentioned, the number of individuals in both Yale and ORL face databases is small. FERET face database is used in this section. We divide the 70 individuals into two groups. Group 1 consists of 30 individuals and is used for selection of classifier in training stage. Group 2 consists of 40 individuals, which are not overlapped in Group 1, is used for testing. DWGNM with estimated probability measure is used in all experiments in this section.

5.4.1. Selection of classifier in training stage

Out of 70, 30 people in Group 1 are used for selection of classifier. The rank 1 to rank 3 accuracies of each method are tabulated in Table 9. It can be seen from Table 9 that the combination accuracy is 90.6667%. That is the $O_a = 90.6667\%$ (please refer to Section 4.1 for definition). For the first iteration, we take one classifier out and combine the rest. The results are shown in Table 10. It can be seen that the highest accuracy is 94.6667%, which is higher than 90.6667% when the PCA method is taken out. So another iteration is performed.

In the second iteration, only three classifiers are left and the experiment is repeated. The results are shown in Table 11. It can be seen that all accuracies are dropped below 94.6667%. This implies that we should keep all the remaining classifiers and the iteration stops. Thus the PCA algorithm is removed and the remaining three methods are kept and used in the recognition stage.

5.4.2. Performance in recognition stage

Using the selected three algorithms in Section 5.4.1, 40 individuals in Group 2 are used to evaluate the performance. The rank 1 to rank 3 accuracies of each method are calculated and tabulated in Table 12. These figures can be used as

Table 9: Results of the FERET database on Group 1 face images.

Method	Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Spectroface	85.3333	89.3333	93.3333
PCA	76.0000	84.0000	87.3333
ICA	81.3333	90.6667	92.6667
Local Gabor wavelet	80.6667	84.6667	88.0000
Sum rule	90.6667	94.6667	96.0000

Table 10: Performance with one classifier removed.

Spectroface	PCA	ICA	Gabor wavelet	Accuracy
×	✓	✓	✓	80.6667%
✓	×	✓	✓	94.6667%
✓	✓	×	✓	94.0000%
✓	✓	✓	×	87.3333%

Table 11: Performance with two classifiers removed.

Spectroface	ICA	Gabor wavelet	Accuracy
×	✓	✓	87.3333%
✓	×	✓	94.0000%
✓	✓	×	93.3333%

a reference. It can be seen that the rank 1 accuracy of each method ranges from 79.5% to 85.5%.

The overall performance in integrating all three proposed idea is shown in the last row in Table 13. The rank 1 accuracy is 92.5%. Comparing with the sum rule with all four classifiers, where the rank 1 accuracy is 90.5%, the proposed method gives a 2% improvement. Comparing with the spectroface, which gives the best result for single algorithm, performance is improved by 7%.

5.5. Microscopic analysis

This section further investigates why combining global and local features can improve the performance. The "right lighting" image Figure 4 and the "sad" image Figure 4 in Yale database are used for demonstration. The first image is selected because it is the hardest image for recognition. Most of the techniques are unable to handle such a poor and nonlinear lighting. This image also shows that the global feature techniques fail to handle illumination problem, while local feature techniques perform well. On the other hand, the second image shows that the local feature fails to recognize the image, while the global feature perform good.

Here, we only extract the detailed ranking of rig.img and sad.img when matching with each of the 15 persons. DWGNM is used and the results are recorded and tabulated in Tables 14 and 15.

In Table 14, the first column indicates the person number, ranging from 1 to 15. The second to fifth columns are the four individual methods. Each entry indicates the rank when the right image is matched with that person. Rank 1 means the right image is correctly recognized, while rank 15 means the poor matching. It can be seen that none of the single individual method provides a satisfactory result.

Table 12: Results of the FERET database on images in Group 2.

Method	Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
Spectroface	85.5000	90.5000	92.0000
ICA	79.5000	83.5000	87.5000
Local Gabor wavelet	82.0000	83.5000	88.5000

Table 13: Overall performance of the FERET database on images in Group 2.

Method	Rank 1 (%)	Rank 2 (%)	Rank 3 (%)
DWGNM + Sum Rule	90.5000	94.5000	95.5000
DWGNM + Classifier Selection algorithm + Weighted combination rule	92.5000	95.0000	95.5000

The four combination rules and our proposed combination schemes are employed and evaluated. The results are tabulated in the sixth to tenth columns. The results show that the performance, in general, can be improved to combine different methods. In particular, sum rule performs the best among the four rules, and data fusion with weighting performs better than that the sum rule. This can be explained that the misclassified image by different classifiers may not be overlapped. If one method misclassifies an image, the other method may compensate the error to get a correct classification. The use of weight function can further improve the classification performance. It can be seen from the results in last column.

Similar results on sad.img are obtained as shown in Table 15. It can be seen that both ICA and Gabor techniques do not give a satisfactory result. However, this error can be compensated by the spectroface and PCA. Finally, correct classification is obtained.

6. CONCLUSIONS

This paper successfully combines local and global features for face recognition. The key factor is how to combine the features. Along this direction, we have addressed three issues in combining classifiers based on Kittler et al. framework and developed solutions in each issue as follows:

(1) the normalization method for combining different classifiers' output;
(2) a classifier selection algorithm;
(3) a weighted combination rule.

We have also demonstrated that the performance integrating all three methods gives a very promising result.

Table 14: Microscopic analysis of the right image.

Class no.	Spectroface	PCA	ICA	Gabor	Sum rule	Product rule	Min rule	Max rule	Weighted combination rule
1	2	12	1	7	3	3	12	2	3
2	1	3	1	1	1	1	1	1	1
3	9	7	1	1	1	1	2	1	1
4	1	2	1	1	1	1	1	1	1
5	1	5	1	1	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1
7	1	2	1	1	1	1	1	1	1
8	1	6	4	1	2	2	1	5	1
9	1	6	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	1
11	1	1	1	1	1	1	1	1	1
12	1	10	1	1	1	1	2	1	1
13	1	1	1	1	1	1	1	1	1
14	1	2	1	2	1	1	1	1	1
15	1	7	4	1	1	1	1	1	1

Table 15: Microscopic analysis of the sad image.

Class no.	Spectroface	PCA	ICA	Gabor	Weighted combination rule
1	1	1	1	1	1
2	1	1	1	1	1
3	1	1	2	1	1
4	1	1	1	1	1
5	1	1	1	1	1
6	1	1	4	1	1
7	1	1	2	1	1
8	1	1	2	7	1
9	1	1	8	1	1
10	1	1	1	1	1
11	1	1	1	1	1
12	1	1	3	1	1
13	1	1	1	1	1
14	1	1	1	1	1
15	1	1	1	1	1

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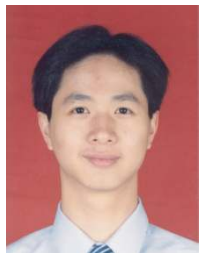

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