A novel face recognition method: Using random weight networks and quasi-singular value decomposition

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ABSTRACT

This paper designs a novel human face recognition method, which is mainly based on a new feature extraction method and an efficient classifier – random weight network (RWN). Its innovation of the feature extraction is embodied in the good fusion of the geometric features and algebraic features of the original image. Here the geometric features are acquired by means of fast discrete curvelet transform (FDCT) and 2-dimensional principal component analysis (2DPCA), while the algebraic features are extracted by a proposed quasi-singular value decomposition (Q-SVD) method that can embody the relations of each image under a unified framework. Subsequently, the efficient RWN is applied to classify these fused features to further improve the recognition rate and the recognition speed. Some comparison experiments are carried out on six famous face databases between our proposed method and some other state-of-the-art methods. The experimental results show that the proposed method has an outstanding superiority in the aspects of separability, recognition rate and training time.

1. Introduction

Face recognition has attracted much attention in recent years due to its inexpensive, convenient and hassle-free advantages. It has widespread applications, such as smart cards, telecommunication, database security, medical records, and digital libraries [27]. There are two key steps in the face recognition: feature extraction and classification. The aim of feature extraction is mainly to give an effective representation of each image, which can reduce the computational complexity of the classification algorithm and enhance the separability of the images to get a higher recognition rate. While the aim of classification is to distinguish those extracted features with a good classifier. Therefore, an effective face recognition system greatly depends on the appropriate representation of human face features and the good design of classifier.

It is well known that image features are usually classified into four classes: Statistical-pixel features, visual features, algebraic features, and geometric features (e.g. transform-coefficient features), where the latter two are often applied in face recognition system. Up to now, many geometric-feature based methods have been proposed to acquire a higher level of separability through transforming the space-domain of the original image into another domain. At the early stage, wavelet transform is popular and widely applied in face recognition system for its multi-resolution character, such as 2-dimensional discrete wavelet transform [6], discrete wavelet transform [8], fast beta wavelet networks [12], and wavelet based feature selection [9,24,26,29]. Although wavelet transform is suitable for detecting singularities in the image, it fails to represent curved discontinuities. Fortunately, Donoho and Duncan have proposed another transform-based method, called curvelet transform, to improve the directional capability [4]. That is, it can represent edges with singularities well and increase anisotropy with decreasing scale as well. Therefore, curvelet transform has been widely used in face recognition, such as curvelet based moment method [14], curvelet based face recognition [15,16], and curvelet based image fusion [21]. On the other hand, the algebraic features of images can reflect the intrinsic properties of images stably. Therefore, they have been considered as valid features for face recognition [10]. As one of the effective algebraic-feature based methods, singular value decomposition (SVD) method [7] was applied in face recognition to extract feature vectors [3,23]. It can represent algebraic features from space-domain well. However, images usually come from the same class in practical applications, so they are often related to each other. Hence it is not enough to just take SVD method in images as SVD method is applied on each image separately.

As we all know, related literatures only use one of the above features in the process of extracting face features. In this paper, we will propose a new method for extracting compound features that consist of geometric features and algebraic features. At first, we use FDCT to
extract geometric features from original images. Considering that the obtained geometric features usually contain statistical redundancies, two dimensional principal component analysis (2DPCA) [25,28] is employed to reduce redundancies as well as to reveal the essential features of face image. At the same time, in order to compensate the shortcoming of SVD method, we propose an improved method, called quasi-singular value decomposition (QSVD) method, to extract algebraic features to represent the relation of each image in a unified framework better. Finally, we fuse the dimensionality-reduced geometric features with the algebraic features by Q-SVD method to form the final compound features. Therefore, these compound features possess not only geometric information, but also algebraic information of images, which can increase separability of images and thus improve the recognition rate greatly.

After extracting the compound features, the following work is to design an effective classifier. There have been a lot of classifiers, such as polynomial function, support vector machine (SVM) [22], and feed-forward neural networks (FNNs). Among these classifiers, FNN can be seemed one of the most popular techniques. As we know, perceptron [19] and backpropagation (BP) algorithm [30] are classical methods for training FNNs. But they are often confronted with the slow learning speed in the process of tuning parameters. However, random weight network (RWN) is proposed in some prior articles [11,17,20] to improve the learning speed of FNNs. That is, the hidden weights and biases are chosen randomly and the output weights of FNNs are calculated by the least square. Compared with the traditional BP algorithm and its various modified methods, RWN has a more concise architecture and a faster learning speed. Therefore, RWN has wide applications in many areas. In this paper, we take RWN as a classifier to distinguish those final compound features to improve the recognition accuracy and speed. After extracting the compound features, the following work is to design an effective classifier.

In Section 2, we propose a novel method for face recognition that contains a method for extracting the compound features and an algorithm for training the classifier. Section 3 gives some experimental comparisons of our proposed method with some other state-of-the-art approaches for face recognition. Finally, conclusions based on the study are highlighted in Section 4.

2. Proposed method for face recognition

In this section, a new method for face recognition is proposed. It consists of two key steps: the extraction of the compound features and a design of an efficient classifier. Specifically, the compound features are made of geometric features and algebraic features. At first, we use FDCT [1] to extract geometric features from original images and employ 2DPCA [25] to reduce their dimensionality for computation. At the same time, in order to compensate the deficiency of geometric features, we propose an improved QSVD method to extract algebraic features to represent the relation of each image in a unified framework better. Finally, we fuse the dimensionality-reduced geometric features with the algebraic features to form the final compound features. At last, we apply the efficient RWN as a classifier to distinguish those final compound features to improve the recognition accuracy and speed. The block schematic diagram of the proposed method for face recognition is shown in Fig. 1.

2.1. Extract geometric features with FDCT and 2DPCA

It is well known that the original face images often need to be well represented instead of being input into the classifier directly because of the huge computational cost. As one of the popular representations, geometric features are often extracted to attain a higher level of separability. Since curvelet transform has an advantage on the directional capability over wavelet transform, here we employ FDCT proposed by Candès et al. [1] to generate the initial geometric features for representing face images.

Suppose that there are \( m \) facial images \( \{F_i\}_{i=1}^{m} \), then the process of extracting geometric features with FDCT via wrapping is as follows:

Geometric features extraction with FDCT via wrapping 2.1.1:

Step 1: For each facial image \( F \), compute its coefficients with 2-dimensional fast discrete Fourier transform (2D-FDFT) to get its representative samples \( \hat{F}(n_1,n_2) \) on the Fourier frequency, where \( F(n_1,n_2) \) denotes the discrete Fourier transform of the function \( F \) at the point \( (n_1,n_2) \), and \(-n/2 \leq n_1, n_2 < n/2\).

Step 2: At each scale \( s \) and angle \( \theta \), form the product \( \hat{U}_{s,\theta}(n_1,n_2) \hat{F}(n_1,n_2) \), where \( \hat{U}_{s,\theta} \) is a localizing window supported on some rectangle of length \( l_{s,1} \) and width \( l_{s,2} \).

Step 3: Wrap this product around the origin and obtain \( \hat{F}_{s,\theta}(n_1,n_2) = \hat{W}(\hat{U}_{s,\theta} \hat{F})(n_1,n_2) \), where the ranges of \( n_1, n_2 \) and \( \theta \) are \( 0 < n_1 < l_{s,1} \), \( 0 < n_2 < l_{s,2} \), and \((-\pi/4, \pi/4)\), respectively.

Step 4: Apply the inverse 2D-FDFT to each \( \hat{F}_{s,\theta} \) and save the discrete curvelet coefficients to obtain the coarse curvelet coefficients matrix \( A \) for the facial image \( F \).

Up to now, we have gotten \( m \) coarse curvelet coefficients matrices \( \{A_i\}_{i=1}^{m} \), i.e. geometric features, of original facial images \( \{F_i\}_{i=1}^{m} \). However, the dimension of each feature matrix is still large, it is necessary to reduce its dimensionality for saving computation cost. Here we adopt 2D-PCA [25] to reduce the dimensionality of the extracted coarse curvelet coefficients matrix.

For the \( m \) coarse curvelet coefficients matrices \( \{A_i\}_{i=1}^{m} \) extracted from \( m \) facial images, let \( \overline{A} \) be their average matrix as follows:

\[
\overline{A} = \frac{1}{m} \sum_{i=1}^{m} A_i.
\]  

So the image covariance matrix \( C \) can be represented as follows:

\[
C = \frac{1}{m} \sum_{i=1}^{m} (A_i - \overline{A})^\top (A_i - \overline{A}),
\]  

and the generalized total scattered criterion \( J(x) \) can be expressed by

\[
J(x) = x^\top C x.
\]  

Fig. 1. Diagram of the proposed method for face recognition.
Let $\mathbf{x}_{opt}$ be the unitary vector such that it maximizes the generalized total scatter criterion $J(\mathbf{x})$, that is

$$\mathbf{x}_{opt} = \arg \max_{\mathbf{x}} J(\mathbf{x}).$$ (4)

In general, there are more than one optimal solution. We usually select a set of optimal solutions $\{\mathbf{x}_1, \ldots, \mathbf{x}_d\}$ subjected to the orthonormal constraints and the maximizing criterion $J(\mathbf{x})$, where $d$ is smaller than the dimension of the coarse curvelet coefficients matrix. In fact, they are those orthonormal eigenvectors of the matrix $C$ corresponding to $d$ largest eigenvalues.

Now for each coarse subband coefficient matrix $A_i$, compute the principal component of the matrix $A_i$ as follows:

$$\mathbf{y}_j = \Lambda_i \mathbf{x}_j, \quad j = 1, 2, \ldots, d.$$ (5)

Then we can get its reduced geometric features matrix $Y_i = [Y_{i1}, \ldots, Y_{im}], i = 1, 2, \ldots, m$. Up to now, we have finished extracting the reduced geometric features $Y_i$ from the original facial image $F_i$, $i = 1, 2, \ldots, m$.

### 2.2. Extract algebraic features with the proposed Q-SVD method

Using the feature extraction with FDCT and dimensionality reduction with 2D-PCA, we mainly captured the geometric features from the original facial images in Section 2.1. However, original facial images often contain abundant algebraic information except that geometric information. So it is important to extract some algebraic features with some techniques to increase separability of images and thus to improve the recognition rate greatly. Generally, the existing methods often apply SVD on each original facial image to get its corresponding singular values that form a feature vector. Its process can be written in mathematics as follows.

For each original facial image $F_i, i = 1, 2, \ldots, m$, there exist two orthogonal matrices $U_i$ and $V_i$ such that

$$F_i = U_i \Sigma_i V_i^T,$$ (6)

where $\Sigma_i = \text{diag}(\lambda_1^{(i)}, \ldots, \lambda_m^{(i)}, 0, \ldots, 0)$ and $\lambda_1^{(i)} \geq \lambda_2^{(i)} \geq \ldots \geq \lambda_m^{(i)} > 0$. Then the corresponding algebraic feature of the image $F_i$ with SVD method is given as

$$\mathbf{z}_i = [\lambda_1^{(i)}, \lambda_2^{(i)}, \ldots, \lambda_m^{(i)}]^T, \quad i = 1, 2, \ldots, m.$$ (7)

SVD is an effective method for extracting algebraic feature from each facial image $F_i, i = 1, 2, \ldots, m$, but these processes are independent. However, facial images sometimes come from the same class in practical applications, that is, they are often dependent on each other. Therefore it is not appropriate to just use SVD in that case. In order to compensate the shortcoming of SVD method, we propose an improved method, Q-SVD method, to extract algebraic features to represent the relation of each image in a unified framework better. Since Q-SVD method considers the dependence of each image based on SVD, it seems to be more logical. Its process can be described as follows:

**Proposed Q-SVD method 2.2.1:**

**Step 1:** For the set of original facial images $\{F_i\}_m^1$, calculate their mean

$$\mathbf{F} = \frac{1}{m} \sum_{i=1}^{m} F_i.$$

**Step 2:** Applying SVD method on the mean matrix $F$ to compute its corresponding orthogonal matrices $U$ and $V$, i.e.

$$\mathbf{F} = \mathbf{U} \Lambda \mathbf{V}^T.$$

**Step 3:** For each original facial image $F_i$ using the obtained orthogonal matrices $U$ and $V$ to calculate the matrix $B_i = \mathbf{U} F_i \mathbf{V}^T, i = 1, 2, \ldots, m$.

**Step 4:** For $i = 1, 2, \ldots, m$, select $p$ largest diagonal elements of the matrix $B_i$ to form the corresponding algebraic feature $\mathbf{z}_i$ of the original image $F_i$.

**Remark 2.2.2.** With Step 1 and Step 2, we get two common orthogonal matrices $U$ and $V$ for all the images in a unified frame since we apply SVD on the mean of all images.

**Remark 2.2.3.** In Step 3, we use the common orthogonal matrices $U$ and $V$ on each image to calculate the matrix $B_i$. It happens that there are some nonzero elements in off-diagonal, but we can find that the nonzero elements in off-diagonal are very small according to experiments. Hence it is instructive to choose $p$ largest diagonal elements of the matrix $B_i$ to form the corresponding algebraic feature $\mathbf{z}_i$ of the original image $F_i$.

**Remark 2.2.4.** When each image is equal, that is $F_i = F_j, i \neq j$, the corresponding algebraic feature $\mathbf{z}_i$ of the original image $F_i$ obtained by Q-SVD is same as that obtained by SVD.

### 2.3. Compound features of geometric features and algebraic features

As we all know, almost related literatures only use one of the features in the process of extracting face features. In order to increase separability of images and improve the recognition rate greatly, we propose a new method for extracting compound features that consist of geometric features and algebraic features in this paper. Up to now, we have obtained the reduced geometric feature $Y_i = [y_{i1}, \ldots, y_{im}]$ and algebraic feature $\mathbf{z}_i$ for the original image $F_i, i = 1, 2, \ldots, m$ in Sections 2.1 and 2.2, respectively. Let $\mathbf{r}_i = [y_{i1}, \ldots, y_{im}, z_{im}]^T$, then $\mathbf{r}_i$ is taken as the compound feature of the original facial image $F_i, i = 1, 2, \ldots, m$.

From the construction of the compound features, they possess of not only geometric information, but also algebraic information of images.

### 2.4. Classify the compound features with RWN

After obtaining those compound features $\mathbf{r}_i$ of the original facial images $F_i, i = 1, 2, \ldots, m$, we need to design an effective classifier to classify them. As we all know, RWN can be seen as one of the most popular classifiers. Because its hidden weights and biases are chosen randomly and its output weights are calculated by the least square, it has a better generalization and a faster learning speed than some traditional training algorithms. In this subsection, we take RWN as a classifier to distinguish those compound features $\mathbf{r}_i, i = 1, 2, \ldots, m$ to improve the recognition accuracy and speed. The concrete process of training RWN by those compound features is as follows.

For the set of sample data $\{(\mathbf{r}_i, \mathbf{t}_i)\}_n^1$, we use the following FNN with $L$ hidden nodes:

$$f(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^{n} \beta_i G(\mathbf{a}_i, \mathbf{b}_i, \mathbf{x}),$$ (8)

to classify those sample data, where $\mathbf{a}_i$ and $\mathbf{b}_i$ are the hidden weights, $\beta_i$ is the output weight connecting the $i$-th hidden node to the output node, and $G(\mathbf{a}_i, \mathbf{b}_i, \mathbf{x})$ is the output of the $i$-th hidden node with respect to the input vector $\mathbf{x}, i = 1, 2, \ldots, L$. Additive hidden node and radial basis function (RBF) hidden node are often used in applications. For the additive hidden node, $G(\mathbf{a}_i, \mathbf{b}_i, \mathbf{x})$ is given by

$$G(\mathbf{a}_i, \mathbf{b}_i, \mathbf{x}) = g(\mathbf{a}_i \cdot \mathbf{x} + b_i),$$ (9)

where $g : \mathbb{R} \to \mathbb{R}$ is an activation function and $\mathbf{a}_i \cdot \mathbf{x}$ denotes the inner product of vectors $\mathbf{a}_i$ and $\mathbf{x}$ in $\mathbb{R}^n$. For the RBF hidden node, $G(\mathbf{a}_i, \mathbf{b}_i, \mathbf{x})$
is given by
\[ G(a_i, b_i, x) = g(b_i \|x - a_i\|), \]
(10)
where \( g : \mathbb{R} \rightarrow \mathbb{R} \) is an activation function, \( a_i \) and \( b_i (b_i > 0) \) are the center and impact factor of \( i \)-th RBF node, respectively.

Now we use the following RWN algorithm [20] to learn all the weights:

**RWN Classifier 2.4.1:** For the set of sample data \( \{(r_i, t_i)\}_{i=1}^m \), take an FNN with \( L \) hidden-layer nodes as in (8), where the hidden-node output function \( G(a, b, x) \) and the hidden-node number \( L \) are chosen in prior.

**Step 1:** Randomly assign hidden-layer weights \( (a^*_n, b^*_n), i = 1, 2, \ldots, L \).

**Step 2:** Compute the hidden-layer output matrix
\[
H = \begin{bmatrix}
G(a^*_1, b^*_1, r_1) & \cdots & G(a^*_1, b^*_L, r_1) \\
\vdots & \ddots & \vdots \\
G(a^*_1, b^*_1, r_m) & \cdots & G(a^*_1, b^*_L, r_m)
\end{bmatrix}_{m \times L}.
\]

**Step 3:** Calculate the output weight vector
\[
\hat{\beta} = H^\dagger T,
\]
where \( H^\dagger \) is the Moore-Penrose pseudo inverse of \( H \), and \( T = [t_1, t_2, \ldots, t_m]^\top \).

**Step 4:** The FNN \( f \) in (8) is determined by
\[
f(x) = \sum_{i=1}^L \hat{\beta}_i G(a^*_i, b^*_i, x),
\]
where \( \hat{\beta} = [\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_L]^\top \).

**Remark 2.4.2.** The number of hidden nodes is chosen to be a small integer initially in applications. If the training error is not good, we can increase hidden nodes to reduce it. Considering the testing error simultaneously, there is a proper number of hidden nodes in applications.

### 3. Experiments

In order to evaluate the performances of our proposed method for face recognition, we carry out face recognition experiments on six famous face databases, including Faces94, JAFFE, Sheffield, ORL, YALE and YALE B. These databases are widely used to evaluate the performances of various face recognition algorithms. Before carrying out our experiments, we first briefly introduce these human face databases used in our paper.

**Faces94 Database** contains images of 152 distinctive individuals with various racial origins, mainly first year undergraduate students between 18 and 20 years old, and each individual has a series of 20 images.

**JAFFE Database** is composed of 220 images of varying facial expressions sampled from 10 Japanese female models.

**Sheffield Face Database** contains 564 images of 20 individuals with mixed race, gender and appearance. Each person has successive pose images varying from left/right profiles to frontal views with small angular rotations. Furthermore, the size of these facial images is uniformly reduced to 112 \( \times \) 92, and the background information is eliminated from input images so that only the central characteristics of the face are retained.

**ORL Face Database** consists of 10 different images for each of the 40 distinct individuals. Each person is imaged in different facial

![Fig. 2. Images from six databases. (a) Face 94 Face Data, (b) JAFFE Face Data, (c) SJAFFE Face Data, (d) ORL Face Data, (e) YALE Face Data and (f) YALE B Face Data.](image-url)
expressions and facial details under varying lighting conditions at different times. All the pictures are captured with a dark background and the individuals are in an upright and frontal position.

YALE Face Database is made up of 11 different gray-scale images for each of the 15 distinct persons. Each individual has a different facial expression or configuration: with/without glasses, left/center/right-light, happy/sad/normal, sleepy, surprised, and winking.

While YALE B Face Database contains 5760 single light source images of 10 subjects each seen under 576 viewing conditions (9 poses $\times$ 64 illumination conditions). For every subject in a particular pose, an image with ambient (background) illumination was also captured (Fig. 2).

### 3.1. Algorithm implementation

In our experiments, the geometric features of training and testing images are produced with FDCT and 2D-PCA. The algebraic features are obtained by our proposed Q-SVD. For each face database as above, we randomly choose a part of images as training data and the remaining as testing data. In this paper, we choose about 50% of each individual’s images as training data and the rest as testing data. All these training and testing data are decomposed with FDCT at 3 scales and 8 different angles, and 25 subband coefficient matrices are acquired. Then the coarse curvelet coefficient matrices are dimensionality reduced with 2DPCA to get the geometric feature for the original image. At the same time, the proposed Q-SVD is applied on all the images to get algebraic features. Then the final compound features are obtained by putting geometric features and algebraic features together. Finally, the final compound features are classified by RWN classifier. The detailed implementation of our proposed method for face recognition is described as follows:

1. Turn each image $F_i$ ($i = 1, \ldots, m$) into gray-level image and resize them uniformly as $l_0 \times w_0$.
2. Compute the corresponding curvelet transform for each training image and obtain the coarse subband coefficient matrix $A_i$ ($i = 1, \ldots, m$), whose size is $l_1 \times w_1$.
3. Calculate the covariance matrix $C$ of training samples and obtain the orthonormal eigenvectors $x_1, \ldots, x_p$ of $C$ with respect to its largest eigenvalues, which are used as projection axes for dimensionality reduction.
4. Obtain $d$ principal components for each sample image $A_i$ by $y_{ij} = A_i x_j$, $j = 1, \ldots, d$, $i = 1, \ldots, m$.
5. Calculate all the algebraic features $z_i$ by Q-SVD, $i = 1, \ldots, m$.
6. Take $\mathbf{r}_i = [y_{i1}, y_{i2}, \ldots, y_{id}, z_i]^T$ as an input vector to train RWN classifier, and $\mathbf{t}_i$ as the output value corresponding to the $i$-th class.
7. Transform the testing images $F_j$ ($j = 1, \ldots, q$) with FDCT to obtain low frequency coarse matrix, and carry out the dimensionality reduction with 2DPCA to get the corresponding principal components column vectors.
8. Put geometric feature vectors and algebraic feature vectors together to get the final compound feature vectors, which are sent to the learned RWN classifier for classification.

The numbers of hidden neurons in RWN are taken to be 2000 in this section except the special note, and the output of hidden node is

$$G(a_i, b_i, x) = g(a_i \cdot x + b_i),$$

where

$$g(t) = \frac{1}{1 + e^{-t}}.$$

All the experiments are carried out in MATLAB R2010a environment running on a desktop with CPU AMD Athlon 2.7 GHz and 1.75 GB RAM.

### 3.2. Experiments

**Experiment 3.2.1.** In this experiment, in order to show the efficiency of our proposed Q-SVD method for extracting algebraic features over SVD, we compare SVD + RWN with Q-SVD + RWN on JAFFE Database with varying numbers of singular values in Table 1.

As shown in Table 1, the recognition rates of our proposed Q-SVD + RWN are obviously higher than those of SVD + RWN, which implies that it is appropriate to extract algebraic features in a unified frame.

**Experiment 3.2.2.** In this experiment, in order to show the efficiency of our applied classifier RWN, we compare it with some other classifiers BP, radial basis function (RBF) [18] and SVM with the same compound features on JAFFE Database with varying numbers of principal components in Table 2.

It can be seen that BP does not work for face recognition because of its high computation cost. Although RBF classifier can achieve almost good recognition rates as RWN, it takes 1000 times running time than RWN. Furthermore, SVM can take smaller training time than RBF, but its recognition rates are not high. In summary, the applied RWN can not only achieve the best recognition rate, but also take the least training time. In the meanwhile, RWN can attain the recognition rate 99.5% with only 5 principal components, and it keeps stable with the increase of principal components.

**Experiment 3.2.3.** This experiment compares the recognition rate of our proposed method with those of some other state-of-the-art approaches on Yale Database. Table 3 shows the corresponding recognition results.

Table 1

<table>
<thead>
<tr>
<th>Number of singular values $p$</th>
<th>Recognition rate (%)</th>
<th>SVD + RWN</th>
<th>Proposed Q-SVD + RWN</th>
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<tbody>
<tr>
<td>5</td>
<td>42</td>
<td>74</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>49</td>
<td>79</td>
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Table 2

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<th>Component</th>
<th>Recognition rate (%)</th>
<th>Training time (s)</th>
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<tr>
<td>BP</td>
<td>99.5</td>
<td>376.7</td>
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<tr>
<td>RBF</td>
<td>99</td>
<td>383.22</td>
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<tr>
<td>SVM</td>
<td>99</td>
<td>378.11</td>
</tr>
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Table 3

<table>
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<tr>
<th>Methods</th>
<th>Recognition rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stand eigenface [13]</td>
<td>76</td>
</tr>
<tr>
<td>Waveletface [5]</td>
<td>83.3</td>
</tr>
<tr>
<td>Waveletface + PCA [16]</td>
<td>84</td>
</tr>
<tr>
<td>Waveletface + LDA [2]</td>
<td>83.5</td>
</tr>
<tr>
<td>Waveletface + weighted modular PCA [26]</td>
<td>83.6</td>
</tr>
<tr>
<td>Curveletface + LDA [16]</td>
<td>83.5</td>
</tr>
<tr>
<td>Curveletface + PCA [16]</td>
<td>83.9</td>
</tr>
<tr>
<td>Waveletface + KAM [24]</td>
<td>84</td>
</tr>
<tr>
<td>Curveletface + PCA + LDA [16]</td>
<td>92</td>
</tr>
<tr>
<td>Our proposed method</td>
<td>93.3</td>
</tr>
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experimental results on Yale Database with 5 principal components.

As shown in Table 3, the recognition rates of our proposed method are obviously higher than those of some other existing face recognition methods.

Since the recognition rate of curveletface þ PCA þ LDA method [16] is better than those of some other existing methods except our proposed method, we can just compare our proposed method with it in the remaining experiments for simplicity.

**Experiment 3.2.4.** This experiment compares the recognition rate of our proposed method with the curvelet based PCA þ LDA method on Sheffield and JAFFE Databases, where we use 5 varying numbers of principal components with 2000 and 1200 hidden nodes, respectively. In addition, similar experiments are also carried out on ORL and Face94 Databases with 4000 and 5000 hidden nodes, respectively. The corresponding experimental results are shown in Tables 4 and 5, respectively.

As observed from Tables 4 and 5, we find that our proposed method consistently outperforms PCA þ LDA based approach for ORL, JAFFE, Sheffield and Face94 Databases. It is noted that the increase of the number of principal components does not necessarily increase the recognition rate.

**Experiment 3.2.5.** In this experiment, we compare the recognition rate and training time of our proposed method with the curvelet based PCA þ LDA method on Face94 Database using varying numbers of principal components. The experimental results are shown in Table 6.

Table 6 clearly validates our claim that the proposed method has superior recognition rate and faster speed than PCA þ LDA based method, and is suitable for real-time applications.

**Experiment 3.2.6.** In this experiment, in order to show the efficiency of good combination of our proposed method, we compare our proposed method with some other combination methods such as FDCT þ PCA þ RWN, FDCT þ 2D-PCA þ RWN and Q-SVD þ RWN on ORL Database with varying numbers of principal components is shown in Table 7.

As observed from Table 7, if we just take algebraic features with Q-SVD, the recognition rates are not ideal. If we just take geometric features with FDCT and PCA or 2D-PCA, the recognition rates are better than Q-SVD þ RWN. However, if we fuse the algebraic features with geometric features, i.e. the proposed method, the recognition rates attain the highest.

**Experiment 3.2.7.** To further validate the performance of our proposed algorithm for face recognition in the case of a larger face database, YALE B face database is employed in this experiment. Here our proposed method is compared with FDCT þ PCA þ RWN and Curveletface þ PCA þ LDA [16] with varying numbers of principal components. The numbers of hidden nodes and singular value are 2000 and 5, respectively.

It is seen from Table 8 that our method has a higher recognition rate than FDCT þ PCA þ RWN and Curveletface þ PCA þ LDA on Yale B face database. FDCT þ PCA þ RWN only obtains 48.68% recognition rate with 5 principal components, while our method still achieves 88.21% recognition rate. The reason is that the dimension reduction and the singular value decomposition in our method obviously enhance the separability for the images with multiple poses and complex illumination.

### 4. Conclusions

A novel human face recognition method was proposed in this paper. The method is mainly based on a new compound feature extraction method and an efficient classifier-random weight network. The extracted compound feature is a fusion of the geometric features and algebraic features of the original image. Here the geometric features are acquired by means of fast discrete curvelet transform and
2-dimensional principal component analysis, while the algebraic features are extracted by a proposed quasi-singular value decomposition method that can embody the relations of each image under a unified framework. Subsequently, the efficient random weight network is applied to classify these fused features to further improve the recognition rate and the recognition speed. Compared with some other state-of-the-art methods in experiments, our proposed method can achieve higher recognition rate and take less training time.

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