FACIAL BIOMETRICS USING NONTENSOR PRODUCT WAVELET AND 2D DISCRIMINANT TECHNIQUES

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A new facial biometric scheme is proposed in this paper. Three steps are included. First, a new nontensor product bivariate wavelet is utilized to get different facial frequency components. Then a modified 2D linear discriminant technique (M2DLD) is applied on these frequency components to enhance the discrimination of the facial features. Finally, support vector machine (SVM) is adopted for classification. Compared with the traditional tensor product wavelet, the new nontensor product wavelet can detect more singular facial features in the high-frequency components. Earlier studies show that the high-frequency components are sensitive to facial expression variations and minor occlusions, while the low-frequency component is sensitive to illumination changes. Therefore, there are two advantages of using the new nontensor product wavelet compared with the

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traditional tensor product one. First, the low-frequency component is more robust to the expression variations and minor occlusions, which indicates that it is more efficient in facial feature representation. Second, the corresponding high-frequency components are more robust to the illumination changes, subsequently it is more powerful for classification as well. The application of the M2DLD on these wavelet frequency components enhances the discrimination of the facial features while reducing the feature vectors dimension a lot. The experimental results on the AR database and the PIE database verified the efficiency of the proposed method.

Keywords: Face recognition; nontensor product wavelet; two-dimensional component analysis.

1. Introduction

Facial biometrics refers to technologies for human authentication based on human facial characteristics. As one of the most popular biometrics, face recognition may not be the most reliable and efficient, but its great advantage is that it does not depend on the test subject. Different from other biometrics like fingerprints, iris, and speech recognition, face images can be expediently collected by mass scanning. It will have many potential applications in public security in the future. However, many present facial biometric systems are unserviceable when identifying the same person with different expressions, aged, from changing viewpoints, with various accessories (moustache, glasses), or in varying illumination. For robustness of recognition, advanced illumination and expression invariant face representation methods are required.

Basically, a face recognition system comprises three key steps: namely, face sample capture, facial feature extraction and template matching. A successful face recognition system depends heavily on the particular choice of features to represent face images, namely good feature extraction, which involves the derivation of salient features from raw input data that have reduced dimensionality together with enhanced discriminatory power. Precise and concise facial feature extraction is crucial and desirable for determining the final recognition accuracy and computational efficiency. Many novel attempts have been made in face recognition since the late 1970s. There are two major approaches for facial feature extraction: geometrical local feature-based schemes (e.g. relying on the relative positions of eyes, nose and mouth) and holistic template-based systems and their variations. The geometrical based schemes can provide flexibility in dealing with nonrigid facial features such as eyes and mouth, but their performance relies heavily on the accuracy of local facial feature detection. In holistic template-matching systems, attempts are made to capture the most appropriate representation of face images as a whole and exploit the statistical regularities of pixel intensity variations. This method considers the face as a global feature, and hence the detection of local features are not required. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are two classical holistic-based techniques. Besides these two, discrete cosine transforms, wavelet transforms, and neural networks also belong
to this category. Specially, wavelet based methods have been reported with good performances in many literatures\cite{6, 10, 13, 15, 36, 51}.

Generally, wavelets applied in face recognition mainly via multiscale wavelet coefficients by 2D discrete wavelet decomposition on face images. At each level of decomposition, four orthogonal subbands corresponding to one low-frequency and three high-frequency components are obtained. These different frequency coefficients capture different visual aspects of the face image with their dimensionality reduced exponentially. Generally, the low-frequency component captures approximative and coarse information of the original image, and the high-frequency components carry detailed or singular information well. Different components are chosen to be directly used or organized to represent facial features. Chien and Wu has proposed a method extracting the three-level lowest-frequency subband as the feature vector, referred to as waveletface\cite{6}, where it is $\frac{1}{8} \times \frac{1}{8}$ of the original facial image in the resolution. However, the direct use of wavelet coefficients may not extract the most discriminative features due to two reasons. On one side, much redundant information may exist in wavelet coefficients. On the other side, the most discriminative features may not be recovered. Therefore, more researchers prefer to extract features from the combinations of wavelet coefficients to overcome these deficiencies. Generally, there are two ways. One is using the statistical quantum of wavelet coefficients in each frequency subband as discriminative features. Garcia et al.\cite{15} presented a wavelet-based framework. Each face is described by a subset of subbands obtained by the two-level wavelet packet transform. A set of simple statistical measures are further used to reduce dimensionality and characterize textural information. After the feature vector formation, the Bhattacharrya distance between two feature vectors is computed for classification. Another popular method is to employ traditional transforms to enhance and extract discriminative features in one or several special frequency subbands. Feng et al.\cite{13} proposed a wavelet subband approach combined with PCA for human face recognition. A three-level diagonal frequency subband is selected for PCA representation, and higher accuracy with low computation was gained when comparing with list using original PCA directly. Ekenel et al.\cite{10} extracted many subband images containing coarse approximations as well as horizontal, vertical and diagonal details of faces at various scales. And then PCA or Independent Component Analysis (ICA) features are extracted from these subbands. At last, different fusion methods have been evaluated to improve recognition. Good performances are shown, especially in case of illumination perturbations. In Ref. 51, a modular face recognition scheme based on wavelet subband representations and kernel associative memories was proposed.

Though wavelet coefficients have been popularly applied in face recognition, some detailed problems are still unfathomed, such as which subband is the best and powerful. Empirical studies show that it is difficult to give a rule to define a certain subband that performs best, especially for the databases with faces in various conditions. When there is a change in human face, some frequency components will be affected. Nastar et al.\cite{28, 29} studied the relationship between facial variations
and their corresponding spectrum. They found that facial expressions and small occlusion only affect the high-frequency spectrum, while changes in illumination affect only the low-frequency spectrum. In other words, high-frequency component is much sensitive to the expression variations and small occlusions, comparatively the low-frequency component remaining is robust to these changes. Whereas in terms of the illuminations variations, high-frequency component is more robust. Therefore, in the case of identifying the same person with varying expressions or small occlusions, low-frequency component is better than high-frequency components, however in the case of the illuminations, it is better to adopt high-frequency components. Some studies empirically verified this conclusion, Ref. 51 denoted that the effect of different facial expressions can be attenuated by removing the high-frequency components, and the low-frequency components alone are sufficient for recognition. Ekenel et al. 10 verified that the horizontal subband got the best performance under varying illuminations.

Up to now, almost all the wavelet based methods use the tensor products of one-dimensional wavelets. Unfortunately, their anisotropic properties 4, 16 implied lots of limitations applied in facial feature representation. The tensor product wavelet transform can detect singular information only from three spatial directions including vertical, horizontal and diagonal. Because of this limited orientation reflection, an enormous amount of singular information which characterizes the face’s irregular structures and transient phenomena deriving from background noises and different expressions cannot be revealed. It implies that a lot of redundant information sensitive to the expression changes are left in the low-frequency components, which results in a low recognition accuracy and high computation complexity as well. With the studying of wavelets, more and more new wavelets 4, 7, 18, 21, 34 which are not composed by direct tensor products of one-dimensional ones have been constructed. Researchers found that the nontensor product wavelet can reveal more singular features than the tensor product ones 4, 7, 18, 21, 34. Subsequently, the nontensor product wavelet is recommended to be applied in facial feature representation. In this paper, new nontensor product bivariate wavelet filter banks with linear phase are employed, which are constructed from the centrally symmetric matrices in our recent work. 4, 47 These filter banks have a matrix factorization and are capable of describing the features of a facial image. In our experiments, we have evaluated the performances of the different frequency components and finally determined to adopt two-level low-frequency coefficients.

In order to further enhance the discrimination of the facial features and reduce computational complexity, a modified two-dimensional linear discriminant technique based on two-dimensional matrices is adopted. As a most famous linear discriminant analysis, the standard PCA represents faces by a linear combination of weighted eigenvectors, which provides a small set of features that carry the most relevant information for classification purposes. However, PCA often gives high similarities indiscriminately for two images from a single person or from two different persons. Yang 44 proposed two-dimensional principle component analysis
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(2DPCA) based on two-dimensional matrices rather than the one-dimensional vectors considered by the traditional PCA, which also get good performances. In this paper, we further present a modified strategy based on 2DPCA. Called a modified two-dimensional linear discriminant (M2DLD) technique, it can represent faces in a lower-dimensional space with more robustness and computational efficiency.

Based on the new constructed nontensor product wavelet and proposed modified two-dimensional linear discriminant (M2DLD) technique, we establish a new scheme for facial feature extraction. To test the efficiency of the implementation of this strategy, support vector machines (SVM) are applied for classification. The SVM is a powerful machine learning approach, owing to its remarkable characteristics such as good generalization performance, absence of local minima, and sparse representation of the solution. It has become a popular research method in anomaly detection with good applications reported in Refs. 14, 20, 22, 27 and 30. The experiments are rigorously carried out on the AR face database and the PIE database. We evaluate the effects of nontensor product wavelet and modified two-dimensional linear discriminant (M2DLD) technique, respectively. The results show the efficiency of the proposed scheme both in recognition rate and executing time.

The rest of this paper is organized as follows. In Sec. 2, we will introduce the proposed method in detail including three subsections. First, the construction of the new nontensor product wavelet filters banks will be reviewed in Sec. 2.1. In Sec. 2.2, the modified 2D linear discriminant technique is described. Subsequently, we will explain the application of the constructed nontensor wavelet and propose the new face recognition scheme in Sec. 2.3. The experimental results will be demonstrated in Sec. 3. The final part is about the conclusions.

2. Face Recognition Based on DNWT and M2DLD

2.1. Construction of nontensor product wavelet filters banks

The construction of wavelets is still an active research topic in both signal and image processing. Our main work here focuses on multivariate filter banks. In particular, the study of the two-dimensional case is crucial for digital image processing. A commonly used method builds multivariate filter banks using the tensor products of univariate filters. However, this construction of filter banks focuses excessively on the coordinate direction. Therefore, nontensor product approaches for construction of multivariate wavelets are desirable. Nevertheless, it is not easy to design multivariate wavelets. There are two fundamental difficulties in the design of the low-pass and high-pass filters which are used for the construction of refinable functions and wavelets, respectively. The first challenge lies in finding trigonometric polynomials that satisfy the perfect reconstruction condition and the second is met when we extend a block unit vector of trigonometric polynomials to a unitary matrix. Most of the current study in multivariate wavelets is devoted to a dilation matrix.
with determinant two, since in this case, only one high-pass filter needs to be constructed and the matrix extension is the same as the univariate two-channel case.7

Here we review the general construction of bivariate nontensor product wavelet filter banks with a linear phase by using the centrally symmetric matrices seen in our other work.3,47 The family of filter banks given there is suitable in this context, although it is difficult to achieve smoothness. These filter banks have a matrix factorization and can be applied to facial representation.

In order to construct two channel filter banks suitable for image processing, we first introduce the concrete construction of centrally symmetric orthogonal matrices of order 4 in Refs. 4 and 47. In fact, any centrally symmetric orthogonal matrix has the following simple parametrization representation

\[
B = \frac{1}{2} \begin{pmatrix}
1 & 0 & 0 & -1 \\
0 & 1 & -1 & 0 \\
0 & 1 & 1 & 0 \\
1 & 0 & 0 & 1
\end{pmatrix} \begin{pmatrix}
\cos \alpha & -\sin \alpha & 0 & 0 \\
\sin \alpha & \cos \alpha & 0 & 0 \\
0 & 0 & \cos \beta & -\sin \beta \\
0 & 0 & \sin \beta & \cos \beta
\end{pmatrix} \begin{pmatrix}
1 & 0 & 0 & 1 \\
0 & 1 & 1 & 0 \\
0 & -1 & 1 & 0 \\
-1 & 0 & 0 & 1
\end{pmatrix}.
\]

(1)

Consequently, we can obtain a constructive characterization of a centrally symmetric orthogonal matrix of order 4 as follows:

\[
Q(\alpha, \beta) : = B = \frac{1}{2} \begin{pmatrix}
\cos \alpha + \cos \beta & -\sin \alpha + \sin \beta & -\sin \alpha - \sin \beta & \cos \alpha - \cos \beta \\
\sin \alpha - \sin \beta & \cos \alpha + \cos \beta & \cos \alpha - \cos \beta & \sin \alpha + \sin \beta \\
\sin \alpha + \sin \beta & \cos \alpha - \cos \beta & \cos \alpha + \cos \beta & \sin \alpha - \sin \beta \\
\cos \alpha - \cos \beta & -\sin \alpha - \sin \beta & -\sin \alpha + \sin \beta & \cos \alpha + \cos \beta
\end{pmatrix}.
\]

(2)

Accordingly, we can present the following examples of the construction of a centrally symmetric orthogonal matrix of order 4, which play an crucial role in the design of nontensor product bivariate filter banks with two channels. The first case is to let \( \alpha = \beta \). Letting \( \alpha = \beta = \frac{\pi}{2} \) and \( \alpha = \beta = \frac{\pi}{4} \) respectively, we have the following order 4 centrally symmetric orthogonal matrix

\[
Q(\frac{\pi}{4}, \frac{\pi}{4}) = \frac{\sqrt{2}}{2} \begin{pmatrix}
1 & 0 & -1 & 0 \\
0 & 1 & 0 & 1 \\
1 & 0 & 0 & 0 \\
0 & -1 & 0 & 0
\end{pmatrix}, \quad Q(\frac{\pi}{2}, \frac{\pi}{2}) = \begin{pmatrix}
1 & 0 & -1 & 0 \\
0 & 1 & 0 & 1 \\
0 & -1 & 0 & 1 \\
0 & 0 & 0 & 0
\end{pmatrix}.
\]

We consider the case with \( \alpha = 0 \) and \( \beta = \frac{\pi}{2} \), we get that

\[
Q(0, \frac{\pi}{2}) = \frac{1}{2} \begin{pmatrix}
1 & 1 & -1 & 1 \\
-1 & 1 & 1 & 1 \\
1 & 1 & 1 & -1 \\
1 & -1 & 1 & 1
\end{pmatrix}.
\]

Thus, the construction conditions of bivariate compactly supported orthonormal multiwavelets using multiresolution analysis (MRA) equivalent to the design of
orthogonal FIR and QMF filter banks is generalized as follows:

(I) Find the low-pass filter \( m_0(\xi, \eta) \) satisfying the orthogonality

\[
|m_0(\xi, \eta)|^2 + |m_0(\xi + \pi, \eta)|^2 + |m_0(\xi, \eta + \pi)|^2 + |m_0(\xi + \pi, \eta + \pi)|^2 = 1,
\]

\((\xi, \eta) \in \mathbb{R}^2, \quad (3)\)

(II) Find three high-pass filter \( m_1, m_2, m_3 \) such that the matrix \( M = (\alpha_0, \alpha_1, \beta_0, \beta_1) \)

is unitary, where \( \alpha_i \) and \( \beta_i \) are the following row vectors

\[
(m_0(\xi + i\pi, \eta), m_1(\xi + i\pi, \eta), m_2(\xi + i\pi, \eta), m_3(\xi + i\pi, \eta))^T,
\]

and

\[
(m_0(\xi + i\pi, \eta + \pi), m_1(\xi + i\pi, \eta + \pi), m_2(\xi + i\pi, \eta + \pi), m_3(\xi + i\pi, \eta + \pi))^T,
\]

\((i = 0, 1)\).

Where the bivariate trigonometric polynomials \( m_{0,l} \) are defined for \( l = 0, 1, 2, 3 \) as

\[
m_0(\xi, \eta) = \sum_{j \in \mathbb{Z}} \sum_{k \in \mathbb{Z}} c_{2j,2k} e^{-i(j\xi + k\eta)},
\]

\[
m_1(\xi, \eta) = \sum_{j \in \mathbb{Z}} \sum_{k \in \mathbb{Z}} c_{2j+1,2k} e^{-i(j\xi + k\eta)},
\]

\[
m_2(\xi, \eta) = \sum_{j \in \mathbb{Z}} \sum_{k \in \mathbb{Z}} c_{2j,2k+1} e^{-i(j\xi + k\eta)},
\]

\[
m_3(\xi, \eta) = \sum_{j \in \mathbb{Z}} \sum_{k \in \mathbb{Z}} c_{2j+1,2k+1} e^{-i(j\xi + k\eta)}.
\]

Both problems (I) and (II) are nonlinear problems in mathematics, which are essentially quadratic algebraic equations with multiple variables. There is no general solution for this problem presently. Here we have proposed a class of solutions of (I) and (II) starting from a centrally symmetric matrix.\(^{47,48}\)

For any fixed positive integer \( N \), arbitrarily choose real number pairs \( (\alpha_k, \beta_k) \), \( k = 1, 2, \ldots, N \) (for \( k \neq j \), \( (\alpha_k, \beta_k) \) may equal to \( (\alpha_j, \beta_j) \)). The low-pass filter \( m_0(\xi, \eta) \) is defined as follows:

\[
m_0(\xi, \eta) = \frac{1}{4}(1, e^{-i\xi}, e^{-i\eta}, e^{-i(\xi + \eta)}) \left( \prod_{k=1}^{N} Q_{(\alpha_k,\beta_k)} D(2\xi, 2\eta) U_{(\alpha_k,\beta_k)}^{T} \right) \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix},
\]

where \( Q_{(\alpha_k,\beta_k)} \) is the centrally symmetric orthogonal matrix defined previously, and the matrix of trigonometric polynomial is defined as follows: \( D(\xi, \eta) = \text{diag}(1, e^{-i\xi}, e^{-i\eta}, e^{-i(\xi + \eta)}) \). It is easy to see that \( m(0,0) = 1 \), which means that \( m_0 \) is a low-pass filter.
Correspondingly, three high-pass filters $m_j$, $j = 1, 2, 3$ with respect to the above low-pass filter $m_0(\xi, \eta)$ are defined as follows:

$$m_1(\xi, \eta) = \frac{1}{4}(1, e^{-i\xi}, e^{-i\eta}, e^{-i(\xi+\eta)}) \left( \prod_{k=1}^{N} Q(\alpha_k, \beta_k) D(2\xi, 2\eta) U^T(\alpha_k, \beta_k) \right) \begin{pmatrix} 1 \\ -1 \\ 1 \\ -1 \end{pmatrix},$$

$$m_2(\xi, \eta) = \frac{1}{4}(1, e^{-i\xi}, e^{-i\eta}, e^{-i(\xi+\eta)}) \left( \prod_{k=1}^{N} Q(\alpha_k, \beta_k) D(2\xi, 2\eta) U^T(\alpha_k, \beta_k) \right) \begin{pmatrix} 1 \\ 1 \\ -1 \\ -1 \end{pmatrix},$$

$$m_3(\xi, \eta) = \frac{1}{4}(1, e^{-i\xi}, e^{-i\eta}, e^{-i(\xi+\eta)}) \left( \prod_{k=1}^{N} Q(\alpha_k, \beta_k) D(2\xi, 2\eta) U^T(\alpha_k, \beta_k) \right) \begin{pmatrix} 1 \\ -1 \\ -1 \\ 1 \end{pmatrix},$$

where $(\xi, \eta) \in \mathbb{R}^2$. It is easy to check that $m_j(0, 0) = 0$, $j = 1, 2, 3$. That is to say, $m_j$, $j = 1, 2, 3$ are high-pass filters.

Once given parameters $\alpha, \beta$ and $N$, filter banks with matrix format will be generated. They can be applied on the face images by 2D convolutions.

**2.2. Modified two-dimensional linear discriminant techniques**

Principle component analysis (PCA) is a classical feature representation technique which has been successfully applied in face recognition. It represents the faces by a linear combination of weighted eigenvectors known as eigenfaces, and the corresponding weight coefficients are called principle components, which are used as the facial features. PCA processes on the lengthened image vectors, which always causes the high-dimension problem that the covariance matrix cannot be evaluated accurately. Although the generally used singular value decomposition (SVD) techniques\cite{19, 39} calculate the eigenvectors efficiently, the essential problem has not been solved. To overcome this awkward situation, Yang\cite{44} proposed two-dimensional principle component analysis (2DPCA), which was based on two-dimensional matrices rather than the one-dimensional vectors. It indicated that 2DPCA evaluates the covariance matrix more accurately and is more efficient than the traditional PCA in terms of both recognition accuracy and computational complexity. In this paper, we present a modified strategy based on 2DPCA to represent the faces in a lower-dimensional space more efficiently. Before introducing our modified two-dimensional linear discriminant (M2DLD) techniques, we give a brief review of 2DPCA.

Given $N$ training face images $X_1, X_2, \ldots, X_N$, each face image matrix has dimension $m \times n$. The traditional PCA treats every face image which is composed of a vector of dimension $mn$, i.e. $x_1, x_2, \ldots, x_N \in \mathbb{R}^{mn}$. PCA projects the original face images onto a low-dimensional subspace by the following projection

$$\chi = U^T x, \quad x \in \mathbb{R}^{mn}$$

(4)
U is spanned by a set of eigenvectors of the total scatter matrix \( S_x \) corresponding to the first \( d \) largest eigenvalues. \( S_x \) is defined as follows

\[
S_x = \frac{1}{N} \sum_{j=1}^{N} (x_j - \bar{x})(x_j - \bar{x})^T
\]

where \( \bar{x} \) is the mean vector of all the training face image vectors \( x_1, x_2, \ldots, x_N \).

Thus, each face is represented as a column vector of dimension \( d \) \((d \ll mn)\).

Opposed to the traditional PCA, two-dimensional PCA is based on two-dimensional matrices rather than one-dimensional vectors. For an arbitrary face image \( X \), an expected \( n \)-dimensional unitary representation vector \( \chi \) is obtained by

\[
\chi = XU, \quad X \in \mathbb{R}^{m \times n}.
\]

With the so-called generalized total scatter criterion, analogous to the traditional PCA, the projection direction \( U \) is found by maximizing the total scatter trace of the projected feature vectors of the training samples, namely \( U = \arg\max(\text{tr}(S_{\chi})) \),

\[
S_{\chi} = \frac{1}{N} \sum_{j=1}^{N} (\chi_j - \bar{\chi})(\chi_j - \bar{\chi})^T, \quad \text{tr}(S_{\chi}) = U^T S_X U
\]

where \( S_X \) is the total scatter of the training face images

\[
S_X = \frac{1}{N} \sum_{j=1}^{N} (X_j - \bar{X})^T (X_j - \bar{X}).
\]

Thus the optimal projection axis \( U \) is obtained as the eigenvector of \( S_X \) corresponding to the largest eigenvalue. In general, \( U \) is selected as \([u_1, u_2, \ldots, u_d]\) rather than a unitary column vector, where \( u_i \) (\( 1 < i < d \)) is the \( i \)th projection direction, which corresponds to the orthonormal eigenvector of \( S_X \) corresponding to the \( i \) largest eigenvalue. Thus each face is represented as a matrix of dimension \( m \times d \) \((d \ll n)\). Compared to the traditional PCA, 2DPCA is more efficient in computation because it reduces the covariance matrix’s dimension from \( mn \times mn \) to \( n \times n \).

Rewrite each training face image matrix \( X_j \) as \( X_j = [X^1_j, X^2_j, \ldots, X^m_j]^T \), with \( X^i_j \) \((1 \leq i \leq m)\) as the \( i \)th row vector of the face image matrix \( X_j \). We deduce the total scatter of the training face images \( S_X \) again

\[
S_X = \frac{1}{N} \sum_{j=1}^{N} (X_j - \bar{X})^T (X_j - \bar{X})
\]

\[
= \frac{1}{N} \sum_{j=1}^{N} \sum_{i=1}^{m} (X^i_j - \bar{X})^T (X^i_j - \bar{X})
\]
\[ = \sum_{i=1}^{m} \left[ \frac{1}{N} \sum_{j=1}^{N} (X^i_j - \bar{X}^i)^T (X^i_j - \bar{X}^i) \right] \]

where

\[ S_{X,i} = \frac{1}{N} \sum_{j=1}^{N} (X^i_j - \bar{X}^i)^T (X^i_j - \bar{X}^i). \]

It is not difficult to find that each \( S_{X,i} \) is the covariance matrix of all the \( i \)th row vectors of the training face images. Therefore, this procedure is actually equivalent to performing traditional PCA on every \( i \)th row vector. In other words, 2DPCA essentially removes the column redundancy of the original face images. In light of this fact, it is reasonable to further reduce the redundancy from rows naturally. Therefore, we realize the new two-dimensional linear discriminant techniques (M2DLD) by three stages:

- **Stage 1**: Perform 2DPCA on face image \( X \in \mathbb{R}^{m \times n} \), acquiring the first stage feature representation \( \chi_{\text{stage1}} \in \mathbb{R}^{m \times d_1} \), \( d_1 \) is the number of eigenvectors chosen.
- **Stage 2**: Transpose \( X \) and then perform 2DPCA on face image \( X^T \in \mathbb{R}^{n \times m} \), acquiring the second stage feature representation \( \chi_{\text{stage2}} \in \mathbb{R}^{n \times d_2} \), \( d_2 \) is the number of eigenvectors chosen.
- **Stage 3**: Combine the two feature representation matrices above as a column vector \( \chi_{\text{stage3}} \in \mathbb{R}^{md_1 + nd_2} \). The vector \( \chi_{\text{stage3}} \) is used as the feature representation of the original face image \( X \).

### 2.3. The proposed face recognition scheme

#### 2.3.1. Nontensor product wavelet applied on face images

The new constructed nontensor product wavelet can detect more singularities in the high-frequency components of a face image than the traditional tensor product one does. Generally, at each level of wavelet decomposition, four orthogonal subbands refer to one low-frequency subband and three high-frequency components are generated. Different frequency components capture different visual aspects of the images. Concretely, the low-frequency component captures approximative (A) and coarse information, while the high-frequency components carry detailed or singular information. In the case of the tensor-product wavelet, the high-frequency subbands are confined to capture facial features from only three orientations corresponding to horizontal (H), vertical (V) and diagonal (D). More in detail, the H and V bands can only record the changes of the face image along horizontal and vertical directions respectively, and the D band shows the diagonal features. Because of the limitation of the orientations reflected, most tensor-product high-frequency
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Fig. 1. (a) Tensor product wavelet decomposition (with “db4” wavelet): approximate subimage (top left), horizontal subimage (top right), vertical subimage (down left), and diagonal subimage (down right), respectively. (b) Nontensor product wavelet decomposition (with parameters $\alpha = 0.1, \beta = 0.9, N = 1$): $m_0$ subimage (top right), $m_1$ subimage (top left), $m_2$ subimage (down left), and $m_3$ subimage (down right), respectively.

In the case of the nontensor product wavelet, the high-frequency subbands can capture more features from various orientations. Similar with the tensor product wavelet decomposition, four subbands are obtained by convoluting with the new constructed nontensor product wavelet filters $m_0, m_1, m_2, m_3$. The $m_0$ component carries low-frequency information, whereas the other three components capture high-frequency information from different directions. As shown in Fig. 1(b), we compare the $m_0, m_1, m_2, m_3$ bands with the A, H, V, D bands respectively, where A, H, V, D bands denote the four components got by tensor product wavelet decomposition, respectively.

- In terms of high-frequency subbands, $m_1, m_2, m_3$ bands clearly capture the profile of the face while nearly no facial features can be seen in the H, V and D bands. It implies that nontensor product wavelet is really capable of capturing more singular information in the high-frequency subbands.
- In terms of low-frequency subband, $m_0$ band is much blurrier than the A band. It is reasonable because the more singular features are removed, the less information are contained in the remained low-frequency subband.

Earlier studies show that the high-frequency components are sensitive to facial expression variations and minor occlusions, while the low-frequency component is sensitive to illumination changes. When identifying a same person with different expressions and minor occlusions, the features that easily be affected by these
factors are removed by the high-frequency components, while the low-frequency features remaining are more robust to these variations. Therefore, the nontensor product wavelet is more efficient than the tensor product one in this case. Simultaneously, in the case of facing illumination changes, the nontensor product high-frequency components are more powerful as well. Here we use facial features obtained by the new discrete nontensor product wavelet transform (DNWT).

2.3.2. Algorithm

The algorithm is summarized as following:

Step 1. Input the training face images, perform two level nontensor product wavelet decomposition with the nontensor product filters constructed in Sec. 2.2 on each face.

Step 2. Select the subimages as the primary feature representation.

Step 3. Perform the modified two-dimensional linear discriminant techniques on these subimages got in Step 2 to obtain the final facial features and save them as the training feature database.

Step 4. Input the testing face images; the same processing as Steps 1–3 is applied. Finally, input the obtained facial feature data into the SVM systems and compute the recognition rate.

In the case of expression invariant system, we adopt the low-frequency component for feature extraction, while for illumination invariant system, the high-frequency components are used.

3. Experimental Results

3.1. Experiment setup and implementation issue

The proposed method was implemented on the AR face database accessible at http://cobweb.ecn.purdue.edu/aleix/aleix_face_DB.html. The AR face database contains 126 subjects and each subject has 26 face images taken in two sessions. For each session, 13 face images with different facial expressions, illumination conditions and occlusions (sun glasses and scarf) were captured. Here, only the nonoccluded images were considered, Fig. 2 shows the samples of two subjects. In our experiment, we sampled face images of 117 people, each person having six facial images chosen from session 1 denoted as rectangles in Fig. 2. Thereinto, the middle two images were used for testing and the remained four for training. All the face images were cropped into 60×60 size. We also conducted the test using the PIE face database accessible at http://www.ri.cmu.edu/projects/project_418.html. This database contains 41,368 images of 68 people, each person under 13 different poses, 43 different illumination conditions, and with four different expressions. Here, we only focused on the images varying with illumination. Figure 3 shows some samples. As the rectangles denote, the first six images were chosen from each subject to
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evaluate the proposed method. The three odd number facial images were used for training and remaining three even number images for testing. All the facial images were cropped into $112 \times 92$ size.

In our experiments, in order to guarantee equitable comparisons, Daubechies wavelet “db4” is adopted for tensor product wavelet decomposition, since “db4” generally got the best performances as reported in Refs. 10 and 13. SVM is a powerful machine learning approach owing to its remarkable characteristics such as good generalization performance, absence of local minima, and sparse representation of solution. A great deal of applications have been reported.\textsuperscript{14, 20, 22, 27, 30}
Our earlier paper also proved its excellent performance, therefore we only adopted SVM as classifier. Our experiments were implemented in a personal computer with Genuine Inete(R)T2300 CPU and 1.5GB RAM and Matlab version 7.0 was used.

As described in former sections, the proposed method mainly included two innovations corresponding to the nontensor product wavelet and M2DPCA. In order to evaluate these two points' efficiency, our experiments were divided into the following three parts.

3.2. Effects of wavelets

In order to evaluate the effects of tensor product wavelets and the constructed nontensor product wavelet applied in face recognition, first we used the wavelet subbands directly for feature extraction and then classified by SVM on the subset of AR database. This is a database mixed with different expressions and lightings. Table 1 shows the recognition rate and the time cost when using the one-level subbands. A, H, V, D respectively represent approximation subband, horizontal subband, vertical subband and diagonal subband, which correspond to $m_0, m_1, m_2, m_3$ subbands in nontensor product wavelet case. As Table 1 shows, the tensor product wavelet was able to correctly recognize most 224 face images, however, the nontensor product one was able to achieve 225. Additionally, the high-frequency subbands by the nontensor product wavelet perform significantly better than the tensor product ones in both recognition rate and executing time. There are two reasons. On one hand, the nontensor product wavelet is capable of capturing more information in high frequency subbands, thus it can extract more discriminant facial features to get higher correctness. On the other hand, the high-frequency subbands can also simultaneously remove more redundant facial features which are sensitive to the expression variations from the low-frequency subband. These two items enhance the efficiency of feature extraction ability of the nontensor product wavelet. However, one-level wavelet coefficients cost a lot of time because the dimension is still very high. We further tested the two-level and three-level subbands' performances. As Tables 2 and 3 show, with the reduction of the dimension, all the recognition rate decreased compared with one-level subbands. Especially in terms of the approximation subband, the nontensor product wavelet achieved 93.16% and 86.32% correctness, which did

<table>
<thead>
<tr>
<th>1-Step Subband</th>
<th>Tensor Product Wavelet (db4)</th>
<th>Nontensor Product Wavelet $(\alpha = 0.1, \beta = 0.9, N = 2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recognition Rate</td>
<td>Executing Time (s)</td>
</tr>
<tr>
<td>A</td>
<td>95.73%/224</td>
<td>166.12</td>
</tr>
<tr>
<td>H</td>
<td>63.68%/149</td>
<td>114.93</td>
</tr>
<tr>
<td>V</td>
<td>70.09%/164</td>
<td>119.51</td>
</tr>
<tr>
<td>D</td>
<td>45.74%/107</td>
<td>125.29</td>
</tr>
</tbody>
</table>

Table 1. Recognition rate and executing time versus one-level wavelet subbands on the AR database.
Table 2. Recognition rate and executing time versus two-level wavelet subbands on the AR database.

<table>
<thead>
<tr>
<th>2-Step Subband</th>
<th>Tensor Product Wavelet (dB4)</th>
<th>Nontensor Product Wavelet $(\alpha = 0.1, \beta = 0.9, N = 2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recognition Rate</td>
<td>Executing Time (s)</td>
</tr>
<tr>
<td>A</td>
<td>95.73%/224</td>
<td>79.00</td>
</tr>
<tr>
<td>H</td>
<td>73.08%/171</td>
<td>43.82</td>
</tr>
<tr>
<td>V</td>
<td>77.78%/182</td>
<td>44.23</td>
</tr>
<tr>
<td>D</td>
<td>59.40%/139</td>
<td>44.20</td>
</tr>
</tbody>
</table>

Table 3. Recognition rate and executing time versus three-level wavelet subbands on the AR database.

<table>
<thead>
<tr>
<th>3-Step Subband</th>
<th>Tensor Product Wavelet (dB4)</th>
<th>Nontensor Product Wavelet $(\alpha = 0.1, \beta = 0.9, N = 2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recognition Rate</td>
<td>Executing Time (s)</td>
</tr>
<tr>
<td>A</td>
<td>93.59%/219</td>
<td>46.72</td>
</tr>
<tr>
<td>H</td>
<td>79.06%/185</td>
<td>27.20</td>
</tr>
<tr>
<td>V</td>
<td>87.61%/205</td>
<td>28.06</td>
</tr>
<tr>
<td>D</td>
<td>71.37%/167</td>
<td>27.65</td>
</tr>
</tbody>
</table>

much worse than the tensor product one with 95.73% and 93.59% respectively. However, the high-frequency subbands continued to do better. This is because with the high-level wavelet decomposition, more and more singular information was lost excessively from the low-frequency subband, which may include some discriminative information that is useful for classification. Nevertheless, two-level and three-level wavelet coefficients reduced execution time a lot.

3.3. Effects of M2DLD

In order to evaluate the feature extraction efficiency of the proposed M2DLD, we compared it with the standard PCA and 2DPCA in both recognition rate and executing time. After applying these techniques directly on the original images, SVM is used for classification. Table 4 demonstrates the performances of the three methods versus the number of eigenvectors. Here, the number of eigenvectors is calculated by the unit 60 pixels, which is the size of the original AR face. For example, if the number of eigenvectors is five, then the final feature vectors input in the SVM have length $60 \times 5 = 300$ pixels. Compared with the three methods, we find that:

1. PCA got a comparable stable performances, however, it cost the longest time. The best result is 95.73% costing 95.37.
2. In allusion to the AR database, 2DPCA is the fastest method, however the recognition rate is generally the lowest among the PCA and M2DPCA methods.
Table 4. Recognition rate and executing time versus PCA/2DPCA/M2DLD on the AR database.

<table>
<thead>
<tr>
<th>Number of Eigenvectors</th>
<th>Recognition Rate</th>
<th>Executing Time (s)</th>
<th>Recognition Rate (%)</th>
<th>Executing Time (s)</th>
<th>Recognition Rate</th>
<th>Executing Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard PCA</td>
<td>10</td>
<td>95.73%/224</td>
<td>146.34</td>
<td>93.59%/219</td>
<td>86.64</td>
<td>96.15%/225</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>95.73%/224</td>
<td>142.28</td>
<td>93.16%/218</td>
<td>84.67</td>
<td>95.73%/224</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>95.73%/224</td>
<td>127.73</td>
<td>94.44%/221</td>
<td>62.81</td>
<td>96.15%/225</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>95.73%/224</td>
<td>112.76</td>
<td>94.02%/220</td>
<td>63.53</td>
<td>94.44%/221</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>95.73%/224</td>
<td>109.48</td>
<td>92.31%/216</td>
<td>54.00</td>
<td>93.50%/219</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>95.73%/224</td>
<td>97.43</td>
<td>91.88%/215</td>
<td>47.39</td>
<td>91.45%/214</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>95.73%/224</td>
<td>95.37</td>
<td>90.17%/211</td>
<td>39.28</td>
<td>91.45%/214</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>94.87%/222</td>
<td>86.59</td>
<td>86.75%/203</td>
<td>29.25</td>
<td>88.46%/207</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>94.87%/222</td>
<td>76.63</td>
<td>83.76%/196</td>
<td>34.85</td>
<td>84.19%/197</td>
</tr>
</tbody>
</table>

3. M2DLD got the 96.15% correctness and 86.50s, which is the highest correctness and the shortest time. In other words, M2DLD got the best performance.

3.4. Performances of the proposed method

From the above experiments, we see that though both the wavelet method and M2DLD are able to reach a comparable high recognition rate, they cost a long time. In order to keep the higher correctness and shorter costing time simultaneously, we combined the two techniques. As described in Sec. 2.3.2, we first adopted two-step wavelet subbands, then further used M2DLD to enhance the facial features, and then classified by SVM. We evaluate the proposed method on two databases. The nonseparable wavelet parameters were set as $\alpha = 0.1, \beta = 0.9, N = 1$.

3.4.1. AR database

The subset of the AR database we adopted was composed of mixed face images with different expressions and minor varying illuminations. The experimental results verified that only the low-frequency subband got the highest correctness compared with the other three high-frequency subbands. To save space, we only demonstrated the results by low-frequency subbands as shown in Table 5. Here, the number of the eigenvectors were calculated with the unit of size $20 \times 20$, which is the size of the two-level wavelet subbands. For example, if the number is 6, it implied that the feature vectors input to SVM classifier has $6 \times 20 = 120$ length. Table 5 shows that the best performance achieved by the nontensor product wavelet is 96.15% and 60.95s, whereas the tensor product wavelet achieved 94.87% in 75.25s.

3.4.2. PIE database

In order to further evaluate the efficiency of the proposed method, we conducted the experiments on the PIE database. Here it mainly focused on the illumination...
Facial Biometrics Using Nontensor Product Wavelet and 2D Discriminant Techniques

Table 5. Recognition rate and executing time by the proposed method on the AR database.

<table>
<thead>
<tr>
<th>Number of Eigenvectors</th>
<th>Tensor Product Wavelet (db4)</th>
<th>Nontensor Product Wavelet</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recognition Rate</td>
<td>Executing Time (s)</td>
</tr>
<tr>
<td>10</td>
<td>94.44%/221</td>
<td>105.78</td>
</tr>
<tr>
<td>9</td>
<td>94.02%/220</td>
<td>90.03</td>
</tr>
<tr>
<td>8</td>
<td>94.02%/220</td>
<td>86.01</td>
</tr>
<tr>
<td>7</td>
<td>94.44%/221</td>
<td>82.60</td>
</tr>
<tr>
<td>6</td>
<td>94.87%/222</td>
<td>75.25</td>
</tr>
<tr>
<td>5</td>
<td>94.02%/220</td>
<td>61.70</td>
</tr>
<tr>
<td>4</td>
<td>94.02%/220</td>
<td>76.29</td>
</tr>
<tr>
<td>3</td>
<td>92.31%/216</td>
<td>44.29</td>
</tr>
<tr>
<td>2</td>
<td>89.32%/209</td>
<td>48.07</td>
</tr>
<tr>
<td>1</td>
<td>76.07%/178</td>
<td>53.84</td>
</tr>
</tbody>
</table>

variations on faces. As Tables 6 and 7 show, the tensor product wavelet achieved highest correctness 99.02% by the horizontal subband, and the nontensor one even achieved 100% by the $m_2$ and $m_3$ subbands. Thereinto, the $m_3$ performed more perfectly and stably, it cost the least time to reach the highest correctness. The results have well verified the following two results:

1. The high-frequency wavelet coefficients got better performances than the low-frequency ones in illumination invariant face representation.

2. The nontensor product wavelet did better and was more stable than the tensor product wavelet.

Table 6. Recognition rate and executing time obtained by the proposed scheme on the PIE database using tensor product wavelet.

<table>
<thead>
<tr>
<th>Number of Eigenvectors</th>
<th>Tensor Product Wavelet (db4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A (%/s)</td>
</tr>
<tr>
<td>5</td>
<td>98.53/14.26</td>
</tr>
<tr>
<td>4</td>
<td>97.55/13.54</td>
</tr>
<tr>
<td>3</td>
<td>96.57/13.54</td>
</tr>
<tr>
<td>2</td>
<td>97.06/10.40</td>
</tr>
<tr>
<td>1</td>
<td>97.06/10.40</td>
</tr>
</tbody>
</table>

Table 7. Recognition rate and executing time obtained by the proposed scheme on the PIE database using nontensor product wavelet.

<table>
<thead>
<tr>
<th>Number of Eigenvectors</th>
<th>Nontensor Product Wavelet</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>m0 (%/s)</td>
</tr>
<tr>
<td>5</td>
<td>94.61/9.82</td>
</tr>
<tr>
<td>4</td>
<td>95.59/9.29</td>
</tr>
<tr>
<td>3</td>
<td>93.14/8.03</td>
</tr>
<tr>
<td>2</td>
<td>92.65/7.48</td>
</tr>
<tr>
<td>1</td>
<td>91.67/10.0</td>
</tr>
</tbody>
</table>
4. Conclusions

In this paper, we have proposed a new facial biometrics, using two-level wavelet coefficients of a new nontensor product wavelet combining with a modified 2D linear discriminative technique for facial feature extraction, and the support vector machines as classifier. The new nontensor product wavelet can capture information by processing all orientations, rather than only three directions as the tensor product wavelet does. Therefore, more singular information can be revealed by the nontensor product wavelet than the tensor product one. Earlier studies show that facial expressions and small occlusion only affect the high-frequency spectrum, while changes in illumination affect only the low frequency spectrum. It implies that the high-frequency wavelet coefficients are sensitive to the expression variations and minor occlusions, while the low-frequency component are sensitive to the illumination changes. By removing the singular information contained in high-frequency components, the remained low-frequency component are more robust for expression invariant recognition. Accordingly, at the same time, the high-frequency components contain more facial features which are necessary for gaining higher accuracy under illumination variations. Besides the application of the new nontensor product wavelet in feature representation, a modified linear discriminant technique is further applied on the wavelet coefficients, which aims to enhance the discrimination of the facial features. The experimental results show the good performances in both recognition accuracy and computational efficiency on the AR database and PIE database.

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