Palmprint recognition using dual-tree complex wavelet transform and compressed sensing

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Abstract—In this paper, based on the dual-tree complex wavelet transform (DT-CWT) and compressed sensing (CS), a novel and high palmprint recognition performance algorithm is proposed. Firstly, DT-CWT, which provide both approximate shift invariance and good directional selectivity, is employed to represent the palmprint image with better preserving the discriminable features with less redundant and computationally efficient. Then the PCA (Principal Component Analysis), based on linearly projecting the image subband coefficients space to a low dimensional feature subspace, is employed to extract the feature of the palmprint images. At last, the robust compressed sensing classification algorithm is used to distinguish the palmprint images from different hands. The experimental results carried on PolyU palmprint database show that the proposed algorithm has better recognition performance than traditional Nearest Neighbor Classification algorithm.

Keywords: palmprint recognition; DT-CWT; PCA; Compressed Sensing;

I. INTRODUCTION

Biometrics is the general approach to recognize the identity of an individual with certain physiological characteristics or behavioral traits. And the biometric technology has played an important role in the field of internet security. In recent years, palmprint recognition has attracted more and more interests and attention due to its advantages such as reliable, low-cost captured device, non-fake and stable line feature, etc [1]. At present, researches on palmprint recognition have focused on the feature extraction of line, texture, statistics and multiple representations. For high resolution (up to 500 dpi), the line-based recognition often worked well on early off-line palmprint images[2]. However, it is difficult to extract the line feature for the lower solution images (less than 100 dpi) in online recognition system. According to the characteristics of palmprint, algorithms based on multiple orientation features are proposed to improve the accuracy in the palmprint automatic authentication system[3-4]. Also, Inspired by the existing biometric algorithms, such as the subspace-based approaches, the Principal Component Analysis (PCA) is also employed to obtain eigenpalms features in the literature of palmprint recognition[5-7].

Gabor wavelet transforms(GWT), are extensively employed to extract biometric image features and has improved its performance in the biometric image recognition systems for its similar characteristics to those of human visual system[8]. Even though palmprint image representation via GWT is optimal in many respects in the biometric field, it has got two important drawbacks to be dealt with since GWT generates much redundant information and burdens heavy computational cost[9]. During the image acquiring process under non ideal conditions, both noise and non-uniform illumination has damaged impact on biometric feature extraction for recognition. Some of multi-resolution framework utilize wavelet analysis that possesses good characteristics of spatial-frequency localization to detect facial geometric structure, e.g., the discrete wavelet transform(DWT)[10]. However, the lack of shift invariance and poor directional selectivity makes DWT difficult to capture the features from the corresponding wavelet coefficients. The DT-CWT, which can improve the directional representation power of wavelet analysis, is proposed for face recognition due to its attractive properties: approximation shift-invariance, orientation selectivity[11]. Unlike the GWT, the implementation of DT-CWT has relatively less computational expense. Thus, complex approximately analytic wavelets (such as DT-CWT) provide an excellent alternative to Gabor representations with the potential to overcome the above mentioned shortcomings of GWT.

Perhaps, the simplest classification scheme is a nearest neighbor classifier to distinguish different biometric image traits [12]. Under this classifier, an image in the test set is recognized (classified) by assigning to it the label of the closest point in the learning set, where distances are measured in the image space. However, it does not work well under varying lighting conditions. Based on a sparse representation computed by 11-minimization, J. Wright et al propose a general classification algorithm for face object recognition. Compared with the traditional recognition algorithm, a sparse representation provides new insights into feature extraction and has superior performance in biometric recognition field[13].

The rest of this paper is organized in the following manner. In Section 2, the dual-tree complex wavelet transform will be introduced, which focuses on a local multiscale representation of palmprint images with good directional selectivity and invariance. Feature extraction using PCA and classification using compressed sensing will be proposed in Section 3. Experimental results on PolyU Palmprint Database are given in Section 4. Finally, conclusions are presented in Section 5.
II. THE DUAL-TREE COMPLEX WAVELET TRANSFORM

Nick Kingsbury introduced the implementation of DT-CWT, and showed it to have the desirable properties of approximate shift invariance and good directional selectivity[11]. The requirement for the dual-tree setting for forming Hilbert transform pairs is the well-known half sample delay condition. The resulting complex wavelet is then approximately analytic. The properties of the DT-CWT can be summarized as (1) approximate shift invariance; (2) good directional selectivity in 2 dimensions; (3) phase information, perfect reconstruction using short linear phase filters; (4) limited redundancy, independent of the number of scales, 2:1 for 1D; (5) efficiency of order-N computation - only twice the simple DWT for 1D. The DT-CWT has the ability to differentiate positive and negative frequencies and produces six subbands oriented in ±15, ±45, ±75. The impulse responses of the filters for the six directional subbands are shown in Fig. 1.

![DT-CWT real part](image1)
![DT-CWT imaginary part](image2)

Fig. 1. Impulse responses of 2-D complex wavelet filters (up), and of 2-D real wavelet filters (bottom), all illustrated at level 4 of the transforms. The complex wavelets provide 6 directionally selective filters, while real wavelets provide 3 filters, only two of which have a dominant direction.

As illustrated in Fig. 2, two classical wavelet trees (with real filters) are developed in parallel, with the wavelets forming (approximate) Hilbert pairs. One can then interpret the wavelets in the two trees of the DT-CWT as the real and imaginary parts of some complex wavelet. The most important property of DT-CWT is that both the trees have the ability to reconstruct the original signal perfectly. Therefore, the inverse DT-CWT can be viewed as the inverse wavelet transform of both the real and imaginary trees. The two obtained signals are calculated by averaging method. And then the final recognition signal is obtained. This is the computation process of forward and backward DT-CWT.

![Fig. 2 The structure of 2-D DT-CWT](image3)

1D Q-shift scheme for dual tree structure is illustrated in Fig. 3. It also possesses the full shift-invariant properties of the constituent 1-D transforms. It can be extended to 2D DT-CWT, which is oriented and approximately analytic at the cost of four-times expansive. The directional selectivity property and low computation are the important factors of using DT-CWT in application of palmprint representation and recognition.

![Fig. 3 The 1-D Q-shift dual tree structure [14]](image4)

III. PALMPRINT RECOGNITION BASED ON DT-CWT AND CS

This section describes the proposed palmprint recognition algorithm using a compressed sensing as a classifier. Firstly, a region of interest (ROI) from the original palmprint image is extracted to deal with the imperfect preprocessing. This process can also roughly align the palmprint images. The DT-CWT will be performed on the ROI parts of the palmprint images. The PCA is used to extract the feature of palmprint images. At last, the compressed sensing classifier is used to classify the palms from different hands.

A. ROI parts of palmprint image

![ROI parts of palmprint image](image5)

(a) (b)
Once the palmprint is captured, it is processed to get the ROI parts of the image, which is a 128x128, for feature extraction and identity recognition. This process will also reduce, to some extent, the effect of rotation and translation of the hand. The detailed determination process can be found in reference[7]. Figure 4 illustrates a ROI (Fig.4.(a)) image cropped from the original palmprint image (Fig.4. (b)).

B. Principle Component Analysis

PCA has been widely used for dimensionality reduction and as linear feature extraction in computer vision. The purpose of PCA is to reduce the large dimensionality of the data space(observed variables) to the smaller intrinsic dimensionality of feature space(independent variables), which are needed to describe the data economically. Result shows that PCA also performs well in various recognition tasks. The PCA is one of the most successful techniques that have been used in image recognition[15].

PCA computes the basis of a space which is a space which is represented by its training vectors yields projection directions that maximize the total scatter across all classes. These basis vectors, actually eigenvectors, computed by PCA are in the direction of the largest variance of the training vectors. PCA techniques, also known as Karhunen-Loeve methods, choose a dimensionality reducing linear projection that maximizes the scatter of all projected samples.

More formally, let us consider a set of N sample images \( \{x_1, x_2, \ldots, x_N\} \) taking values in an n-dimensional image space, and assume that each image belongs to one of c classes \( \{X_1, X_2, \ldots, X_c\} \). Let us also consider a linear transformation mapping the original n-dimensional image space into m-dimensional feature space, where m<n. The new feature vectors \( y_k \in \mathbb{R}^m \) are defined by the following linear transformation:

\[
y_k = W^T x_k \quad k=1,2,\ldots,N
\]

Where \( W \in \mathbb{R}^{m \times n} \) is a matrix with orthonormal columns. If the total scatter matrix \( S_T \) is defined as

\[
S_T = \sum_{k=1}^{N} (x_k - \mu)(x_k - \mu)^T
\]

Where \( n \) is the number of sample images, and \( \mu = \mathbb{E}(x) \) is the mean image of all samples, then after applying the linear transformation \( W^T \), the scatter of the transformed feature vectors \( \{y_1, y_2, \ldots, y_N\} \) is \( W^T S_T W \).

In PCA, the projection \( W_{opt} \) is chosen to maximize the determinant of the total scatter of the projected samples, i.e.,

\[
W_{opt} = \arg \max_W \|W^T S_T W\| = [w_1, w_2, \ldots w_m]
\]

Where \( \{w_i\} \) is the set of n-dimensional eigenvectors of \( S_T \) corresponding to the \( m \) largest eigenvalues. These eigenvectors have the same dimension as the original images.

In classical PCA technique, an image matrix should be mapped into 1-D vector in advance. Various PCA versions have also proposed to improve the recognition performance, such as 2DPCA[4] and (2D)²PCA[5]. The 2DPCA is introduced to generate a projection space while extracting the projected feature of each image on the space. However, they also have their own drawbacks. The 2DPCA method can directly extract feature matrix from the original image matrix. Therefore, 2DPCA evaluates the image covariance matrix more accurately and computes the corresponding eigenvectors more efficiently than PCA. By simultaneously considering the row and column directions, (2D)²PCA was developed for efficient face representation and recognition in [5]. For recognition, even though (2D)²PCA is more computationally efficient than both PCA and 2DPCA.

C. Compressed Sensing for Classification

Sparse representation, which are representations that account for most or all information of a signal with a linear combination of a small number of elementary signals, has proven to be an extremely powerful tool for representing natural images. Finding a representation with a small number of significant coefficients can be solved as the following optimizing problem[16]:

\[
\hat{x}_0 = \arg \min \|x\|_0 \text{ subject to } Dx = y
\]

Where \( \| \cdot \|_0 \) denotes the \( \ell^0 \)-norm, which counts the number of nonzero entries in a vector. Seeking the sparsest solution to \( Dx = y \) is a NP problem. The theory of sparse representation and compressed sensing reveals that if the solution \( x_0 \) sought is sparse enough, the solution of the \( \ell^0 \)-minimization problem is equal to the solution to the \( \ell^1 \)-minimization problem.

Given sufficient training palmprint samples of the \( i \)-th object hand class, \( D_i = [d_{i,1}, d_{i,2}, \ldots, d_{i,n}] \in \mathbb{R}^{mv} \), a test palmprint sample \( y \in \mathbb{R}^m \) from the same hand will approximately lie in the linear span of the training palmprint samples associated with object \( i \). \( y = D_i x_i \) for some coefficient vector \( x_i \in \mathbb{R}^n \).

Therefore, given a new test palmprint sample feature \( y \) from one of the classes in the training feature set, we first compute its sparse representation via basis pursuit. Usually, the small nonzero entries in the estimation associated with the columns of \( D \) from a single object class \( I \), and can easily assign the test palmprint feature \( y \) to that class. Based on the prior sparse representation of palmprint images, one can treat the test feature can be treated as a linear combination of all
training features of each object. And, one can identify the right class from multiple possible classes. It can be computed as follows:

For each class \( i \), let \( \lambda_i : \mathbb{R}^n \rightarrow \mathbb{R}^n \) be the characteristic function which selects the coefficients associated with the \( i \)-th class, one can obtain the approximate representation \( \hat{y}_i = D\lambda_i(\hat{x}_i) \) for the given test sample \( y \). We then classify \( y \) based on the approximations by assigning it to the object class that minimizes the residual between \( y \) and \( \hat{y}_i \):

\[
\min_{i} r_i(y) = \| y - D\lambda_i(\hat{x}_i) \|_2
\]

\[\text{(13)}\]

D. The proposed palmprint recognition algorithm

The ultimate purpose of the proposed palmprint recognition framework can be mainly divided into the following steps, as illustrated in Fig.5:

- **Step 1:** For reliable feature measurements, the gaps between the fingers as reference points to determine a coordinate system is used to extract the region part of a palmprint image.
- **Step 2:** The preprocessed palmprint image is transformed by DT-CWT to obtain multiple levels magnitude response of DT-CWT in the same directions \( \pm 15, \pm 45, \pm 75 \). The obtained image is four times of the original size.
- **Step 3:** The PCA is employed to reduce dimension and extract the feature of the DT-CWT domain palmprint images efficiently. PCA uses the eigenvectors of the covariance matrix. The eigenpalms are obtained for further processing.
- **Step 4:** The eigenpalms are then calculated by compressed sensing to measure the most similarity to the test palmprint features set. The smallest values can be identified the right hand.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

In PolyU Palmprint Database, there are 600 gray scale images captured from 100 different palms by a CCD-based device[17]. The problems of compressed sensing and L1 minimization are solved by tool box Toolbox Sparse (http://www.ceremade.dauphine.fr/~peyre/matlab/). Six samples from each palm are collected in two sessions: the first three samples were captured in the first session and the other three were captured in the second session. The average time interval between these two sessions was two months. The size of all the images in the database was 384 × 284 with a resolution of 75dpi. In our experiments, a central part (128×128) of each image is extracted for further processing.

The feature vector of the input palmprint is matched against all the stored templates and the most similar one is obtained as the recognition result. The first three samples of each palm are selected for training, and the remaining three samples are used for testing. Following these schemes, we have calculated recognition rates with the dimensions ranging from 5 to 100. The experimental results are shown in Fig.6. As we can see from this Fig.6, the correct recognition rate increases with the increasing of the number of training sample, and it reaches over 90% when the dimension equals to or exceeds 35. The Fig.4 also suggests that the recognition rate of our proposed method (Ours) has better performance than DT-CWT+PCA+NN (a nearest neighbor classifier) under the same condition.

![Fig.6. Recognition rates on PolyU palmprint database](image)

In order to investigate the recognition performance in the present of noise, we also make the palmprint recognition experiments at the noise level equal with 50, also illustrated in Fig.6. From the Fig.6, the CS classification method has superior performance than that of NN. Fig.7 gives a clear view about noise corruption. The most of palmprint has been blurred at so high noise level (standard deviation is 50, variance is 2500). At this level, we can not distinguish different palmprints correctly using our eyes. However, the proposed algorithm still obtains better performance.
Fig. 7. (a) original palmprint image, (b) blurry palmprint image with noise level equal with 50.

Table 1 gives the comparisons of two methods on recognition accuracy, dimensions of feature vector under [5, 10, 20, 30] x [5, 10, 20, 30]. Table 1 shows that the compressed sensing based classification algorithm obtains better recognition accuracy than NN on (2D)2PCA.

<table>
<thead>
<tr>
<th>Recognition dimension</th>
<th>5</th>
<th>10</th>
<th>20</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>CWT+PCA+NN</td>
<td>63.67%</td>
<td>71.67%</td>
<td>75.00%</td>
<td>77.00%</td>
</tr>
<tr>
<td>DT-CWT</td>
<td>78.33%</td>
<td>82.33%</td>
<td>84.00%</td>
<td>85.33%</td>
</tr>
<tr>
<td>PCA</td>
<td>84.67%</td>
<td>86.67%</td>
<td>85.67%</td>
<td>81.33%</td>
</tr>
<tr>
<td>CS</td>
<td>70.33%</td>
<td>79.00%</td>
<td>83.33%</td>
<td>84.00%</td>
</tr>
<tr>
<td>CS2PCA</td>
<td>85.33%</td>
<td>86.67%</td>
<td>81.33%</td>
<td>88.33%</td>
</tr>
<tr>
<td>CS2PCA+NN</td>
<td>71.00%</td>
<td>80.67%</td>
<td>84.00%</td>
<td>80.67%</td>
</tr>
<tr>
<td>CS2PCA+NN</td>
<td>82.00%</td>
<td>88.33%</td>
<td>87.67%</td>
<td>89.67%</td>
</tr>
</tbody>
</table>

In our experiment, five kinds of experimental schemes are designed: the first one (two, three, four or five) sample(s) of each palmprint is selected as the training set, and the remaining sample(s) are used for testing set. The experiment is divided into two parts: one is the original image set and the other is the blurred palmprint images set. Following these different conditions, we have calculated recognition rates with the 50 feature dimensions, as shown in Tab. 2. From Tab. 2, We can find that the recognition rate is increased with the increasing of training sample. The performance of our proposed algorithm is always better than the DT-CWT+PCA+NN. When the training is four, the recognition rate of our proposed algorithm is 100%.

<table>
<thead>
<tr>
<th>Training sample increased (feature dimensions: 40)</th>
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</thead>
<tbody>
<tr>
<td>Algorithms</td>
</tr>
<tr>
<td>------------</td>
</tr>
<tr>
<td>original</td>
</tr>
<tr>
<td>CWT+PCA+NN</td>
</tr>
<tr>
<td>The proposed algorithm</td>
</tr>
<tr>
<td>noise level(50)</td>
</tr>
<tr>
<td>CWT+PCA+NN</td>
</tr>
<tr>
<td>The proposed algorithm</td>
</tr>
</tbody>
</table>

V CONCLUSIONS

In this paper, a novel and high performance palmprint recognition approach using DT-CWT and compressed sensing is proposed. DT-CWT is firstly employed to efficiently represent the palmprint for its approximation shift-invariance, orientation selectivity, efficient computation, then, PCA is applied to further reduce the dimension of DT_CWT coefficients’ matrix. The CS classifier, which enhances the class-discriminatory information in the lower-dimensional space, is used to improve the classification rate and measure the similarity of low-dimension feature values. Experimental results on PolyU Palmprint Database have shown its superior performance than the traditional nearest neighbor classifier.

REFERENCES