Personal authentication by palmprint using contourlet transform and k-nearest neighbour classifier

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Abstract: Biometric-based personal verification is a powerful security feature. Biometric systems are used the physiological and/or behavioural characteristics in each individual for verification. Palmprint is a reliable biometric that can be used for identity verification because it is stable and unique for every individual. In this paper, a new approach for personal authentication by palmprint using contourlet transform is presented. Contourlet transform is a multiscale and directional transform that captures image curvatures and smoothness with multidirectional decomposition capability, finely. Our proposed method includes three steps, preprocessing, feature extraction, and classification. In preprocessing stage, the central part of each palmprint is extracted. In feature extraction step, at first, contourlet transform is applied to the central part of palmprint and then features are extracted from created subbands. In this method for each image, 384 features are obtained. Finally, in classification step, naïve Bayes, support vector machine (SVM) and k-nearest neighbour (k-NN) classifiers are employed. Experiments are performed on three databases and recognition accuracies of 99.41%, 92.38%, and 85.34% are obtained on PolyU, COEP and IITD databases using k-NN algorithm, respectively. Experimental results illustrate that our proposed method could be used effectively in personal authentication by palmprint images.

Keywords: biometric; palmprint recognition; contourlet transform; k-nearest neighbour, k-NN.

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1 Introduction

Nowadays, many applications require reliable verification methods to verify the identity of a person. One of these methods is biometric. Biometric systems recognise individuals based on their physiological and/or behavioural characteristics. Therefore, two main categories of biometrics are ‘physiological’ and ‘behavioural’. Physiological category includes the physical human traits such as peppermint, hand shapes, fingerprint, face, iris, eyes, veins, etc. The behavioural category includes the movement of the human, such as hand gestures, speaking style, signature, voice, gait etc. (Zhang et al., 2003; Kong et al., 2005).

Authentication methods based on a token and password, etc. can be forged, stolen, or forgotten. In addition, person’s friends can easily access token or can guess the password. Nevertheless, biometric characteristics cannot be forged, borrowed, stolen, or forgotten (Delac and Grgic, 2004).

Each biometric characteristic has its own advantages and limitations. Among different biometric authentication techniques, palmprint recognition is one of the most reliable personal identification methods because features are extracted from a large palm area and the palmprint has stable and unique characteristics that remain unchanged on throughout life (Jin et al., 2008). There are a large number of unique features in a palmprint image such as principal lines, wrinkles, ridges, minutiae points, singular points, and textures, which can be used for personal identification (Bong et al., 2010).

Palmprint researches are carried out by using either high resolution or low-resolution images. High-resolution images are used for forensic applications such as criminal detection. Low-resolution images are more suitable for civil and commercial applications such as access control (Ardabili et al., 2011). In comparison with other physical characteristics, palmprint authentication has several advantages (Zhang et al., 2007):

1 low complexity
2 low-resolution imaging
3 stable line features
4 high accuracy
5 high user acceptance
In this paper, a new method for personal authentication by palmprint using contourlet transform (CT) is proposed. In this method, at first the central part of palmprint is extracted. For feature extraction, CT is applied on the central part of palmprint. Consequently, the image is divided into subbands. Afterward, features are extracted from subbands. This approach results higher recognition accuracy compared to previous methods.

The rest of this paper is organised as follows: In Section 2 related works are described. In Section 3, three palmprint databases are introduced. Section 4 explains CT. The proposed method is discussed in Section 5. In Section 6, experimental results are presented and finally, the conclusions are described in Section 7.

2 Related works

A large number of methods have been presented in palmprint recognition. In this section, some of these methods have been reviewed.

Chen et al. (2007) have been presented a method for palmprint recognition by extracting the edges from palm images and then applying CT or the discrete wavelet transform (DWT) on the edge extracted images. The subband images are divided into $M \times M$ non-overlapping blocks. The energy of each block is calculated and normalised to form a feature vector. Then principal component analysis (PCA) is employed where the approximation images are input to it for dimensionality reduction.

Sharkas et al. (2010) have been proposed a method for palmprint recognition. Firstly, it extracts the region of interest (ROI) from the palmprint image by finding a tangent of curves between fingers. The features extracted from the ROI are used for matching. Two approaches are suggested for the feature extraction. In the first approach, the ROI is divided into a suitable number of non-overlapping windows from which fuzzy features are extracted. In the second approach, multi-scale wavelet decomposition is applied on the ROI which is generated several subbands. Then energy feature for each subband is extracted. Finally, two sets of features are used for matching.

Ben Khalifa et al. (2013) have been presented an authentication system based on the palmprint. Three feature extraction techniques based on DWT, Gabor filters and the co-occurrence matrix are proposed in this method. Support vector machine (SVM) is used for the classification task. The results have been validated on PolyU database and the best results have been achieved with the wavelet decomposition.

Hanmandlu et al. (2011) in their authentication system firstly, ROI is extracted from the palmprint image. Then for the purpose of feature extraction, ROI is divided into a suitable number of non-overlapping windows of different sizes and three types of features based on sigmoid, energy and entropy are extracted. These three sets of features are used for the authentication of users using Euclidean distance and SVM as the classifier.

Tunkpien et al. (2010) have been proposed a method to extract the principle lines of palmprint. This method is based on applying a cascade of consecutive filters. Smoothing filter is used as the preprocessing step to discard noise. Derivative filter and closing filter are applied for finding the location of principle lines. In addition, connected component labelling is finally used as the post-processing step to remove the noise generated in between the process.
The research in Hong et al. (2015) proposes to use multispectral palmprint instead of natural light palmprint, and develops a multispectral palmprint recognition method based on a hierarchical idea. First, it extracts the block dominant orientation code as a rough feature, and the block-based histogram of oriented gradient as a fine feature. Second, a hierarchical recognition is employed using these two types of features.

Saedi and Charkari (2014) proposed a texture-based approach to palmprint recognition based on a 2D discrete orthonormal S-transform. This approach characterises the frequency contribution of image texture in the various bandwidths. In this method, First, 2D-DOST is applied to the palmprint to characterise the frequency content of palmprint texture. Palmpprint features are obtained by computing the local energy of 2D-DOST magnitudes in different bandwidths. Then the dimension reduction is done to reduce the dimensionality and eliminate the redundant features.

Table 1 shows the summary of previous related works. Type of feature extraction, number of features, classification method, database employed for evaluation and the resulted accuracies are listed in this table.

<table>
<thead>
<tr>
<th>Year</th>
<th>Ref.</th>
<th>Feature extraction</th>
<th>Feature vector dimension</th>
<th>Classification method</th>
<th>Database</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>Dale et al. (2009)</td>
<td>Discrete cosine transform</td>
<td>-</td>
<td>Canberra distance</td>
<td>A set includes 500 images of 50 persons</td>
<td>97.5</td>
</tr>
<tr>
<td>2011</td>
<td>Malik et al. (2011b)</td>
<td>Gabor filter</td>
<td>49</td>
<td>Hamming distance</td>
<td>A subset of PolyU includes 600 images of 100 persons</td>
<td>96.20</td>
</tr>
<tr>
<td>2011</td>
<td>Malik et al. (2011a)</td>
<td>Phase congruency</td>
<td>20</td>
<td>Hamming distance</td>
<td>A subset of PolyU includes 600 images of 100 persons</td>
<td>97.3</td>
</tr>
<tr>
<td>2012</td>
<td>Vijilious and Bharathi (2012)</td>
<td>CT</td>
<td>48</td>
<td>k-NN</td>
<td>A subset of ASIA includes 800 images of 100 persons</td>
<td>99</td>
</tr>
<tr>
<td>2011</td>
<td>Kekre et al. (2011)</td>
<td>Discrete cosine transform</td>
<td>48</td>
<td>SVM</td>
<td>A subset of IITD includes 100 images of 20 persons</td>
<td>99</td>
</tr>
<tr>
<td>2012</td>
<td>Zhang et al. (2012)</td>
<td>Fragile bits</td>
<td>-</td>
<td>Hamming distance</td>
<td>A subset of PolyU includes images of 192 persons</td>
<td>86.04</td>
</tr>
</tbody>
</table>
Table 1  
Review of previous related works (continued)

<table>
<thead>
<tr>
<th>Year</th>
<th>Ref.</th>
<th>Feature extraction</th>
<th>Feature vector dimension</th>
<th>Classification method</th>
<th>Database</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2013</td>
<td>Ben Khalifa et al. (2013)</td>
<td>Wavelet transform</td>
<td>-</td>
<td>SVM</td>
<td>PolyU</td>
<td>95.20</td>
</tr>
<tr>
<td>2015</td>
<td>Hong et al. (2015)</td>
<td>Block dominant orientation code and the block-based histogram of oriented gradient</td>
<td>-</td>
<td>A hierarchical classifier</td>
<td>PolyU multispectral palmprint database</td>
<td>96</td>
</tr>
</tbody>
</table>

3  Databases

Three palmprint image databases are used in this research for evaluation of the proposed method. These are PolyU, COEP and IITD palmprint databases. These databases are introduced in the following subsections.

3.1  PolyU palmprint database

The PolyU palmprint database has been provided by Hong Kong Polytechnic University (2006). This database contains 7,752 greyscale images corresponding to 386 different palms in BMP image format. Around 20 samples from each of these palms were collected in two sessions, where around 10 samples were captured in the first session and the second session, respectively. The average interval between the first and the second collection was two months. The resolution of all the original palmprint images is $384 \times 284$ pixels at 75 dpi. Some of PolyU palmprint images are shown in Figure 1.

Figure 1  Some of PolyU palmprint images (see online version for colours)
3.2 IITD palmprint database

IITD palmprint database mainly consists of hand images collected from the students and staff at IIT Delhi, India (Kumar, 2007). This database has been acquired in the Biometrics Research Laboratory during January 2006 to July 2007 using a digital CMOS camera. The acquired images were saved in bitmap format. Resolution of the captured images is $800 \times 600$ pixels.

This database contains left and right hand images from more than 230 subjects, using a very simple touchless imaging setup. All the subjects in the database are in the age group 14–56 years and voluntarily contributed at least five hand image samples from each of the hands. In addition to the acquired whole hand images, automatically segmented and normalised palmprint regions are also made available. Some of IITD palmprint images are shown in Figure 2.

Figure 2 Some of IITD palmprint images (see online version for colours)

Figure 3 Some of COEP palmprint images (see online version for colours)
3.3 COEP palmprint database

The COEP palmprint image database is from the College of Engineering, Pune-411005 (an Autonomous Institute of Government of Maharashtra) (http://www.coep.org).

This palmprint database consists of total 1,344 images pertaining to 168 people. The database consists of eight image samples of single person’s palm. The database was collected over a period of one year. The images were captured using a digital camera and were saved in JPG format. The resolution of the images is $1,600 \times 1,200$ pixels. The project is being funded by ‘Rajiv Gandhi Science and Technology Commission’. Some of COEP palmprint images are shown in Figure 3.

4 Contourlet transform

CT was developed by Do and Vetterli (2005) to overcome the limitations of wavelets. CT is a directional transform, which is capable of capturing contours and fine details in images. Contourlet expansion is composed of basis function oriented in various directions in multiple scales, with flexible aspect ratios (Do and Vetterli, 2005). With this rich set of basis functions, CT effectively, captures smooth contours that are the dominant features in palmprint images (Ardabili et al., 2011).

CT is mainly based on the Laplacian pyramid (LP) and the directional filter banks (DFBs). In the LP, the input image will be divided into the lowpass subband and the highpass subband. Then, the lowpass subband will be down sampled in horizontal and vertical directions and passed to the next stage. The highpass subband will be further separated into several directions by the DFBs (Lu and Do, 2006; Liu et al., 2006).

In CT, the LP does the decomposition of images into subbands and then the DFBs analyse each detail image. Figure 4 shows a flow graph of CT. It consists of two major stages: subband decomposition and directional transform. In the first stage, LP and in the second stage, DFB is applied (Liu et al., 2006).

Figure 4 A flow graph of CT (see online version for colours)

Source:  Ardabili et al. (2011)
In the double filter bank structure, LP is used to capture the point discontinuities and then followed by a DFB, which is used to link these point discontinuities into linear structures. DFB is implemented by using a $k$-level binary tree decomposition that leads to $2^k$ directional subbands with wedge shaped frequency partitioning as shown in Figure 5 (Liu et al., 2006).

**Figure 5** DFB frequency partitioning (see online version for colours)

Combination of LP and DFB gives a double filter bank structure known as contourlet filter bank. Bandpass images from the LP are fed to DFB so that directional information can be captured. The scheme can be iterated on the coarse image. This combination of LP and DFB stages result in a double iterated filter bank structure known as pyramidal directional filter bank (PDFB). The PDFB decomposes the given image into directional subbands at multiple scales (Ardabili et al., 2011; Lu and Do, 2006). PDFB structure is shown in Figure 6.

**Figure 6** PDFB structure (see online version for colours)

*Source: Lu and Do (2006)*
5 Proposed method

Our proposed method for palmprint verification includes three stages, preprocessing, feature extraction, and classification. Figure 7 shows the structure of the proposed method and describes the relationship between the three stages. Each stage is further described in the following.

Figure 7 Structure of the proposed method (see online version for colours)

5.1 Preprocessing

One of the most important stages of palmprint recognition methods is preprocessing which must be done before the feature extraction stage. To reduce the overhead, instead of directly using the palmprint images, preprocessing needs to be done. Preprocessing is used to remove useless parts of the palmprints and to crop the central region of the palm. Then the cropped central region of the palm is used for feature extraction. Preprocessing steps are shown in Figure 8.
Figure 8 Preprocessing steps (see online version for colours)

- Binarising the Original Image
- Distance Transform Calculation
- Calculate the centric point of palm
- Crop the central region of palm

Figure 9 The main steps of preprocessing, (a) original image (b) binary image (c) distance transform calculation (d) the central point of palmprint (e) central part extraction (see online version for colours)
Preprocessing is done in four steps as follows:

**Step 1** Apply a low-pass filter, such as Gaussian, to the original image as shown in Figure 9(a) and use a threshold, $T_p$, to convert the original image into a binary image as shown in Figure 9(b). Equation (1) shows the decision process to convert the original image to a binary image.

\[
B(x, y) = \begin{cases} 
1, & \text{if } O(x, y) \ast L(x, y) \geq T_p \\
0, & \text{if } O(x, y) \ast L(x, y) < T_p 
\end{cases}
\]  

(1)

where $B(x, y)$ is a binary image, $O(x, y)$ is an original image and $L(x, y)$ is a lowpass filter like a Gaussian all in the frequency domain.

**Step 2** In this stage, first binarised palmprint is complemented and then distance transform is calculated. The resulted image of this step is shown in Figure 9(c). For each pixel in the binary image, the distance transform assigns a number that is the distance between that pixel and the nearest non-zero pixel.

**Step 3** The maximum distance obtained from the distance transform is calculated and is estimated as the centre of the palmprint. Figure 9(d) shows the centre of palmprint.

**Step 4** Finally, a square region is cropped around the calculated centre of palmprint as shown in Figure 9(e).

### 5.2 Feature extraction

Feature extraction is a very important step in the design of a palmprint verification system. In feature extraction stage, firstly, CT is applied on the central part of palmprint and then features are extracted. The large number of coefficients generated from CT is not need to be used in the classification step because with increasing the number of features, the computation time is increased too. Moreover, it is not true that classification accuracy will improve with increasing the number of features.
In our proposed method, levels 2 and 3 of contourlet decomposition are applied on the central part of palmprint. Considering an image of size 128 × 128 pixels resulted at Step 4 of preprocessing, at level 2, 4 subbands of size 32 × 32 pixels and at level 3, 8 subbands of sizes 32 × 64 and 64 × 32 pixels are obtained. In addition, 12 subbands of sizes 32 × 32, 32 × 64 and 64 × 32 pixels are generated. Figure 10 shows the result of applying levels 2 and 3 of contourlet decomposition as synthetic on central part of palmprint.

After applying CT, in 32 × 32 and 32 × 64 pixels subbands the mean absolute deviation value of coefficients in each row and in 64 × 32 pixels subbands the mean absolute deviation value of coefficients in each column are computed and are used as features.

In this method, from each subband, 32 features are extracted and since with applying contourlet decomposition, 12 subbands are generated, therefore for each image 384 features are obtained. This feature vector is used for classification. The mean absolute deviation value of each row or column of the subbands is calculated by equation (2).

\[
d = \frac{1}{n} \sum_{i=1}^{n} |x_i - \overline{x}|
\]

where \( n \) denotes the number of elements in each row or column of subband, \( x_i \) is the coefficient value at position \( (i) \) of each row or column, \( \overline{x} \) is the mean of values in each row or column, and \( d \) is the mean absolute deviation. Then each computed mean absolute deviation value is used as an element to form a feature vector.

Figure 10  The result of applying levels 2 and 3 of contourlet decomposition on the central part of palmprint (see online version for colours)
5.3 Classification

Classification algorithms include two main phases; in the first phase, they try to find a model for the class attribute as a function of other variables of the datasets, and in the second phase, they apply previously designed model for the new and unseen datasets for determining the related class of each record (Tan et al., 2006).

After feature extraction, classification is used to accept or reject of palmprint images. In this paper, k-nearest neighbour algorithm (k-NN) is used for classification.

Nearest neighbour classifier is based on learning by analogy, that is by comparing a given test tuple with training tuples which are similar to it. The training tuples are described by n attributes. Each tuple represents a point in an n-dimensional space. In this way, all of the training tuples are stored in an n-dimensional pattern space. When given an unknown tuple, k-NN classifier searches the pattern space for the k training tuples, which are closest to the unknown tuple. These k training tuples are the k-NN of the unknown tuple (Han and Kamber, 2006).

‘Closeness’ is defined in terms of a distance metric, such as Euclidean distance that calculates distance between two tuples. Euclidean distance between two points or tuples \( p \) and \( q \) obtained using equation (3).

\[
d(p, q) = \sqrt{\sum (p_i - q_i)^2}
\] (3)

The basic steps of the k-NN algorithm are (Kantardzic, 2003):

1. Compute the distances between the new sample and all previous samples.
2. Sort the distances in increasing order and select the \( k \) samples with the smallest distance values.
3. Apply the voting principle. A new sample will be added (classified) to the largest cluster out of \( k \) selected samples.

6 Experimental results

The proposed method has been implemented in MATLAB. To evaluate the proposed method in this paper, experiments are performed on the three palmprint databases: PolyU, IITD and COEP databases.

The training and test datasets are selected according to the ten-fold cross validation strategy. In this strategy, the dataset is divided into ten parts that nine parts are used as the training set and one part is used as the test set. This process is repeated ten times. Then one of the sampled images is used as the test sample and the remaining images are used as training samples.

In our proposed method, first in preprocessing stage the central part of palmprint with size of 128 \( \times \) 128 pixels is extracted. With applying levels, 2 and 3 of contourlet decomposition as synthetic on the central part of palmprint, 12 subbands are generated and for each subband, 32 features are extracted. Then for each image, 384 features are obtained that is used for classification by k-NN classifier.

The experiments are done on Intel core i-5-2450, CPU 2.50 GHz, 6 GB RAM, 2 GB GPU and Windows 7 Ultimate 32 bit.
Table 1 shows the recognition accuracy of the proposed method on three databases. According to the performed experiments, recognition accuracies of 99.41%, 92.38%, and 85.34% are achieved on PolyU, COEP and IITD databases, respectively using k-NN classifier. Figure 12 shows and compares the accuracy of the proposed method on three databases using a diagram. Table 2 presents the feature execution time of a palmprint image in our proposed method and compares it with the ones of other methods. Accuracy of the proposed method on three databases is compared to the accuracies of other previous methods and the results are depicted in Table 4. As Table 4 shows, our proposed method has higher performance compared to other methods. Some methods are evaluated on unknown non-free dataset and the results are reported in the paper. In this regards, our method is not comparable with these techniques.

Table 1  Results of proposed method on three different databases

<table>
<thead>
<tr>
<th>Database name</th>
<th>Recognition accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PolyU</td>
<td>99.41 %</td>
</tr>
<tr>
<td>COEP</td>
<td>92.38 %</td>
</tr>
<tr>
<td>IITD</td>
<td>85.34 %</td>
</tr>
</tbody>
</table>

Figure 12  Accuracy of the proposed method on three databases (see online version for colours)

Table 2  Comparison of feature execution time of the proposed method with other methods

<table>
<thead>
<tr>
<th>Reference</th>
<th>Feature execution time (mSecs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ben Khalifa et al. (2013)</td>
<td>850</td>
</tr>
<tr>
<td>Zhang et al. (2003)</td>
<td>63</td>
</tr>
<tr>
<td>Guo et al. (2009)</td>
<td>40</td>
</tr>
<tr>
<td>Zhang et al. (2010)</td>
<td>36</td>
</tr>
<tr>
<td>Proposed method</td>
<td>13.6</td>
</tr>
</tbody>
</table>

Table 3 shows the results of experiments, which had been done using three datasets and Bayes, K-NN and SVM classifiers.
Table 3 The results of the proposed method on three databases using tree classifiers

<table>
<thead>
<tr>
<th>Database</th>
<th>No. of features</th>
<th>Classification method – accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>SVM</td>
</tr>
<tr>
<td>PolyU</td>
<td>384</td>
<td>99.28</td>
</tr>
<tr>
<td>IITD</td>
<td>384</td>
<td>99.28</td>
</tr>
<tr>
<td>COEP</td>
<td>384</td>
<td>86.67</td>
</tr>
</tbody>
</table>

Table 4 Results of the proposed method on three databases in comparisons to other methods

<table>
<thead>
<tr>
<th>Reference</th>
<th>Feature extraction type</th>
<th>Classification algorithm</th>
<th>Database</th>
<th>Recognition accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sharkas et al. (2010)</td>
<td>CT</td>
<td>Euclidean distance</td>
<td>120 palm sample pertaining to 24 people</td>
<td>94.00%</td>
</tr>
<tr>
<td>Ben Khalifa et al. (2013)</td>
<td>DWT</td>
<td>SVM</td>
<td>PolyU</td>
<td>95.20%</td>
</tr>
<tr>
<td>Malik et al. (2011a)</td>
<td>Phase congruency</td>
<td>Hamming distance</td>
<td>A subset of PolyU includes 600 samples pertaining to 100 people</td>
<td>97.30%</td>
</tr>
<tr>
<td>Dale et al. (2009)</td>
<td>DCT</td>
<td>Canberra distance</td>
<td>500 samples pertaining to 50 people</td>
<td>97.50%</td>
</tr>
<tr>
<td>Ribaric and Lopar (2012)</td>
<td>Co-occurrence matrix</td>
<td>K-NN</td>
<td>1,874 palm sample pertaining to 243 people</td>
<td>98.91%</td>
</tr>
<tr>
<td>Proposed method</td>
<td>CT</td>
<td>K-NN</td>
<td>PolyU</td>
<td>99.41%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>COEP</td>
<td>92.38%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>IITD</td>
<td>85.34%</td>
</tr>
</tbody>
</table>

7 Conclusions

This paper proposed a new method for personal authentication by palmprint using CT. CT is a multiscale and directional transform that captures image curvatures and smoothness. In the preprocessing step, the central part of palmprint is cropped. For feature extraction, CT is applied on the central part of palmprint. CT divides the original image to soybeans and provides important attributes for palmprint recognition. In our proposed method, 12 subbands are generated and 32 features for each subband are extracted. Therefore, for each palmprint image, 384 features are obtained. Finally, k-NN classifier is used for classification.

Experiments are performed on the three palmprint databases: PolyU, IITD and COEP databases and recognition accuracies of 99.41%, 92.38% and 85.34% are obtained on PolyU, COEP and IITD databases, respectively.
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