A Fast Personal Palm print Authentication based on 3D-Multi Wavelet Transformation

* A. H. M. Al-Helali, *W. A. Mahmmoud, and *H. A. Ali

*Al- Isra Private University

Email: adnan_hadi@yahoo.com

Abstract:
In recent years several palmprint representations have been proposed for personal authentication, but there is no agreement on which palmprint representation can provide best representation for reliable authentication. The development of accurate and robust palmprint authentication is a great important issue in a lot of criminal detection and commercial applications. In this paper, a novel and fast palmprint authentication technique is proposed using 3-D discrete multiwavelet Transform as feature extractor and a probabilistic artificial neural network (PNN) as a classifier. This proposed technique considers the palmprint image as a piece of texture and applies 3-D multiwavelet filters to extract texture information and the texture information of the palmprint images are compared in terms of their vector distance. The system was implemented and tested using a dataset of 240 samples of palmprint data with different contrast quality, size and rotation. The experimental results illustrate that the proposed method achieved a higher genuine acceptance rate and a lower false acceptance rate simultaneously.

Keywords: Biometrics; palmprint; authentication; classifiers; Neural Network; 3D-Multiwavelet.

1. Introduction:

Palmprint, the inner surface of palms, has rich features including principal lines, wrinkles, minutiae points, singular points and texture. These features can be used for uniquely identifying a person. Currently, there are two types of palmprint research, high resolution approach and low resolution approach. High resolution approach is suitable for forensic applications while low resolution approach is suitable for commercial applications [1].

Some researchers report impressive results even using simple methods for palmprint recognition. For example, Palm Code, a palmprint identification algorithm directly applying Iris Code to palmprints, was developed by A.K. Kong and D. Zhang, [2, 8]; the maximum identification rate from these papers not more than 99%.

X. Wu, and D. Zhang, has been shown that palmprint recognition based on Fisherpalms with identification rate of 99.55% in a database with 3,000 images from 300 different palms based on LDA [9, 12]; G. Lu, and D. Zhang Characterized palmprints by wavelet signatures via directional context modeling and report an identification rate of 99.15% in a database with 3056 images from 382 palms based on PCA [10, 16]. X.Y. Jing and D. Zhang address identification rates of only 71.34% for PCA and 90.91% for LDA from a database with 3040 images from 190 palms [11]. It should be pointed out that Jing et al’s implementations are slightly different from Wu et al’s and Lu et al’s implementations.
In this paper, a new accurate palmprint authentication algorithm has been proposed based on the results of 3D-MWLT transform and Probabilistic Neural Network (PNN). The 3D-MWLT feature extraction algorithm identifies the orientation palmprints effective powerful features. This feature is ignored by previous palmprint research. The probabilistic neural network (PNN) is used for training and classification phases. This was used also in the second phase of the proposed system, which is the authentication phase.

The proposed algorithm is tested and evaluated upon a database of (240) palmprint images, which consist of (30) persons eight images for each person which were different in sizes, noise and rotation. These palmprint images were divided into two groups (120) for training and (120) for testing. An overall authentication rate of 100% was achieved. A code for the algorithm is examined through theoretical analysis and computer simulation using MATLAB version 7.

The rest of this paper is organized as the follows. Section 2 describes briefly palmprint database Section 3 presents an overview of the proposed palmprint recognition including, palmprint capture, preprocessing, feature extraction, classification, authentication in large databases and security. Section 4 discusses performance evaluation test, comparison and privacy issues related to palmprint recognition. Section 5 offers some concluding remarks.

2. Palmprint Database
The most important step in the authentication task is the generation of the data base. In this paper a data base of 240 individual’s palmprint images were collected using CCD-based scanner device [8]. These corresponding to 30 persons each person have a total of eight palmprint images with different (noise, rotation, and shift) from left and right palms. These are distributed on a wide spread spectrum of different prototypes. In this database, 15 persons are male, and 15 persons are female and the age distribution of the subjects is: about 24 persons are younger than 30, about 4 persons are aged between 30 and 50, and about 2 persons are older than 50. The size of all the test images used in this data base was 384×284 with a resolution of 75dpi. The aim here was to include versions that consists some sort of rotation and noise that makes the data natural and can be used to check and compare the algorithm and methods that will be proposed here.

3. The Proposed Recognition Method:
The general block diagram of the proposed palmprint recognition system is presented in a block diagram of Figure (3.1). It is clear that this palmprint recognition system consists of four main steps, namely:
   Step (1): Palmprint capture
   Step (2): Image Pre-processing.
   Step (3): Feature extraction.
   Step (4): Classification.
3.1 Palmprint Capture
Palmprint capturing is used to align different palmprint images and to segment the central parts for feature extraction. Most of the palmprint capture algorithms employ the following generally five common steps,
1) Binarizing the palm images,
2) Extracting the contour of hand and/or palms,
3) Detecting the key points,
4) Establishing a coordination system and
5) Extracting the central parts.
Figure 3.2(a) illustrates the key points and Figure 3.2(b) shows a captured image. The first and second steps in all the previous algorithms are similar [1].

3.2 Image Preprocessing
The procedure of generating palmprint image set is given below:
**Step-1:** After extracting the central part of gray palm print image of any size
**Step-2:** Palmprint pre-processing.

The palmprint image is formed of including principal lines, wrinkles, minutiae points, singular points and texture. These palmprint images, stored in database, are not of quality, therefore these images must undergo some pre-processing first after resizing the
input palmprint to size of (256 × 256 pixels) to make all the palmprints of the same size and to reach the result with fast response. Palmprint image processing can be implemented by using some filters and enhancement in order to prepare it to the feature extraction steps.

**Step-3:** Image enhancement (Edge Detection and Smoothing)

Using Laplacian Edge Detector:

Edges boundary detection is a problem of fundamental importance in image processing. Edge detection of an image significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image.

**Step-3:** Segment the Palmprint image into 64 blocks of (32 × 32) pixels as shown in figure 3.3.

Because some part of palmprint may be lost after preprocessing step, so in order to classify them, for much better performance the palmprint image will be segmented into blocks of (32 × 32) pixels, it is necessary to deal with each part as a unique image. This size is selected since it is dependent in several applications like image compression and texture identification. So, the final size of the palmprint is still (256 × 256).

![Figure 3.3 Segment the Palmprint image into 64 blocks of (32 × 32) pixels.](image)

### 3.3 Feature extraction

After passing the data through preprocessing step, which will lead to having a group of 3-D matrices, each matrix will be of (256×256×4) dimension. It is required first to use these data as training phase.

The following algorithm was used for the computation of 3-D discrete multi wavelet transform on multi wavelet coefficients matrices using GHM four multi filter and using an over-sampled scheme of preprocessing (repeated row preprocessing):

a. **Checking Matrix Dimensions:** 3D–Matrix (N×N×M) should be a square matrix, N×N matrix, and must be a power of 2. So that checking input matrix dimensions is the first step of the transform procedure. If the signal is not a square matrix and not a power of two, in this work, this point is satisfied by default, because the previous step (preprocessing) is to be treated this point and generate a 256×256×4 matrix as shown in figure 3.4.
b. Applying 2-D Multiwavelet Transform:
As shown in figure 3.5, Here it is required to apply the two dimensional discrete multiwavelet transform to each N×N input matrix, (i.e. applying 2-D DMWT no. of Z-time, in all the M matrices (N×N) in z-direction.
Note that the 2-D DMWT is a critically-sampled scheme of preprocessing, thus, the result matrix is N×N×M (i.e. 256×256×4).

c. Applying 1-D DMWT Transform: In this step, it must obtain one dimensional discrete Multiwavelet transform (1-D DMWT) on a vector 256×256 (65536 elements) in all M matrices in the z-direction. Now, a N×N×2M matrix results from the N×N×M original matrix using repeated row preprocessing as shown in figure 3.6 and which can be done as follows:-
I. For each i construct the M×1 input vector
   M2(i) = [ ai  bi  ci  di ]t1×M
   where i=1,2,3,…,65536
II. Preprocess the input vector M2 (i) by repeating the input stream with the same stream multiplied by a constant α = 1/√2. In other words, after row preprocessing on an input vector (1×M), the result is (1×2M) matrix. The odd rows 1,3,…,2M-1 of this resultant matrix are the same original vector rows value 1,2,3,…,M respectively. On the other hand, the even rows number 2,4,…,2M are the original signal rows values multiplied by α. Thus :
   M3(i) = [ ai  α.ai  bi  α.bi  ci  α.ci  di  α.di ]t1×M
III. Construct an $M \times M$ transformation matrix using GHM low and high pass filter matrices respectively. After generating GHM matrix filter coefficients values, an $2M \times 2M$ transformation matrix results with the same dimensions of input matrix dimensions after preprocessing.

IV. Apply matrix multiplication to the $2M \times 2M$ constructed transformation matrix by using the $2M \times 1$ preprocessing input vector.

1. Repeat step c for all i
2. Now getting the $256 \times 256 \times 8$ matrix from last step,

![Figure 3.6](image)

Figure 3.6 Rearrange $2M \times 1$ matrix results after applying 1-DMWT

4. Removing the repeated matrices the next step is removing the positive slices (2,4,6,8) and then the only four $256 \times 256 \times 4$ remain, $M4$ is the resulting matrix, as present in figure 3.7.

![Figure 3.7](image)

Figure 3.7 palmprint images after single level of 3D-DMWT using repeated row preprocessing.

3.4 Classification
A Probabilistic Neural Network [14] shown in figure 3.8 is used as a classifier after training it on all coefficients matrices resulted from applying the 3D-DMWT algorithm for all palmprints in the database. The output nodes of NN represents the person number, for example, the vector of person number (1) is $[1-1-1-1-1-1-1-1]^T$, The second person will be $[-11-1-1-1-1-1-1]^T$. This process is repeated for 8 persons to be authenticated. He should have his own signal output neuron. Thus "1" must be active for input matrix of the given person,
and a negative "-1" output for other persons. Parameters uses in NN training are [14]:

- Performance function is MREG.
- Number of hidden layers is 3 layers, and no. of neuron are:
  i. Neurons in the input layer,
  ii. Neurons in the 1st hidden layer,
  iii. Neurons in the 2nd hidden layer,
  iv. Neurons in the 3rd hidden layer,
  v. Neurons in the output layer.
- Epochs is 40000.
- Goals is 1e-06.

![Figure 3.8 PNN classifier architecture](image1)

Figures 3.9 show the training of the Probabilistic Neural Network with 3D-MWLT

![Figure 3.9 Training of the NN for 3D-MWT](image2)

### 4. Evaluation Tests of the Proposed Algorithm using PNN:

For the proposed algorithm, (8) left and right palmprints with different contrast quality, size and rotation should be selecting for each person for the training phase. These data consist of eight palmprints [(p1Z1) to (p1Z8)] respectively. The original images are taken from the database of Hong Kong Polytechnic University and all of them are gray scale of a tiff image file format. The algorithm consists of 240 images of palmprint, the reference set 120 palmprints of them are used to learn the network and the 120 palmprints are used for testing the proposed algorithm. For example, consider the first row of table (4.1) have the training (reference) data with specific sequence of palmprint image, namely (p1z1, p1z2, p1z3, p1z4). The first
column has the testing data with another specific sequence of fingerprint (p1z6, p1z7, p1z8, pz9). When applying the 3D-MWLT algorithm and PNN on the entire 8 persons out of 8 persons. The correct recognition rate is 100% successes.

Table (4.1)

<table>
<thead>
<tr>
<th>The Reference Pattern</th>
<th>F1z-F2z</th>
<th>F1z-F3z</th>
<th>F1z-F4z</th>
<th>F1z-F5z</th>
<th>F1z-F6z</th>
<th>F1z-F7z</th>
<th>F1z-F8z</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1z-F2z</td>
<td>0.9911</td>
<td>-0.9979</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-0.9959</td>
<td>-1.0000</td>
<td>-0.9834</td>
</tr>
<tr>
<td>F1z-F3z</td>
<td>-1.0000</td>
<td>0.9882</td>
<td>-0.9629</td>
<td>-0.9826</td>
<td>-1.0000</td>
<td>-0.9553</td>
<td>-0.9998</td>
</tr>
<tr>
<td>F1z-F4z</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>0.9427</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-1.0000</td>
</tr>
<tr>
<td>F1z-F5z</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-0.9999</td>
<td>0.9842</td>
<td>-0.9989</td>
<td>-0.9999</td>
<td>-0.9748</td>
</tr>
<tr>
<td>F1z-F6z</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>0.9929</td>
<td>-1.0000</td>
<td>-0.9998</td>
</tr>
<tr>
<td>F1z-F7z</td>
<td>-0.9567</td>
<td>-0.9921</td>
<td>-1.0000</td>
<td>-0.9706</td>
<td>-1.0000</td>
<td>0.9970</td>
<td>-0.9996</td>
</tr>
<tr>
<td>F1z-F8z</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-0.9999</td>
<td>-1.0000</td>
<td>0.9851</td>
</tr>
<tr>
<td>F1z-F9z</td>
<td>-0.9957</td>
<td>-0.9995</td>
<td>-1.0000</td>
<td>-1.0000</td>
<td>-0.9999</td>
<td>-1.0000</td>
<td>0.9979</td>
</tr>
</tbody>
</table>

5. Conclusions:
A new method of palmprint image recognition was implemented and tested based on the 3D-MWLT Transform and Probabilistic Neural Network. The following points can be concluded:
The proposed method gave an excellent performance even if the palmprint image is contaminated with noise, contrast quality, size and rotation. The experimental results for image recognition give more accurate result than the individual that formed from it.

References:
