Contourlet Features Extraction and AdaBoost Classification for Palmprint Verification

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Abstract: Biometrics-based personal verification is a powerful security features in technology era. Palmprint is an important complement and reliable biometric that can be used for identity verification because it is stable and unique for every individual. This paper presents a new palmprint verification method by using the contourlet features and AdaBoost classification. The contourlet transform is a new two dimensional extension of the wavelet transform using multi-scale and directional filter banks. It can effectively capture smooth contours that are the dominant features in palmprint images. AdaBoost is used as a classifier in the experiments. Experimental results shows that the contourlet features when classify by using AdaBoost (α-Type) classifier are very suitable for invariant palmprint verification. The experimental results illustrate the effectiveness of the method proposed.
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1. Introduction

Biometric systems that recognize individuals based on their physiological and behavioral characteristics such as the fingerprint, face, iris, palmprint, retina or signature are much more secure [1, 12, 13]. Biometric identification is an emerging technology that can solve security problems in our networked society [4, 5, 16]. In the networked society there are a great number of systems that need biometric identification, so it has become an important issue in our days. This identification can be based on palmprint features [10].

Biometrics have gained much attention in the security world recently, and the use of biological features as the personal identification number has replaced the use of digits gradually due to their obvious advantages. However biometrics can provide a perfect solution to these problems [2].

Biometrics is taking its place as one of the most secure, flexible and reliable of the available approaches [6]. As a result, many biometric systems for commercial applications have been successfully developed [2, 3].

Biometrics-based personal identification is a powerful security features in the technology era [12]. Recently, the researches on biometrics-based verification have been receiving more and more attention because of its stabilization, uniqueness and arduous duplicate characteristics [7].

As the important implementation of biometric technology, palmprint verification is one of the most reliable personal identification methods [5, 8, 9].

Palmprint is one of the relatively new physiological biometrics due to its stable and unique characteristics. The rich texture information of palmprint offers one of the powerful means in the field of personal recognition [2]. There are many unique features in a palmprint image that can be used for personal identification. Principal lines, wrinkles, ridges, minutiae points, singular points, and texture are regarded as useful features for palmprint representation (see Figure 1) [3, 11, 12, 13, 14, 16].

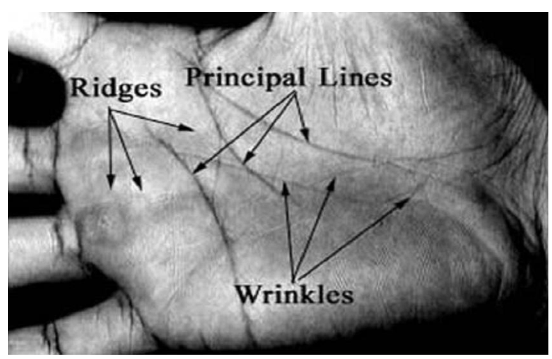

Figure 1. Three types of basic features in a palmprint

Compared with the other physical characteristics, palmprint authentication has several advantages: (1) low-resolution imaging, (2) low intrusiveness, (3) stable line features, (4) high user acceptance, (5) user friendly, and (6) low cost requirements [3, 5, 11, 13, 15].

Palmprint verification is an approach for verifying a palmprint input by matching the input to the claimed identity template stored in a database.

If the dissimilarity measure between the input and the claimed template is below the predefined threshold value, the palmprint input is verified possessing same identity as the claimed identity template [11].

Our palmprint verification system contains three modules, preprocessing, feature extraction and classification. Figure 2 gives a block diagram to describe the relationship between the three modules.

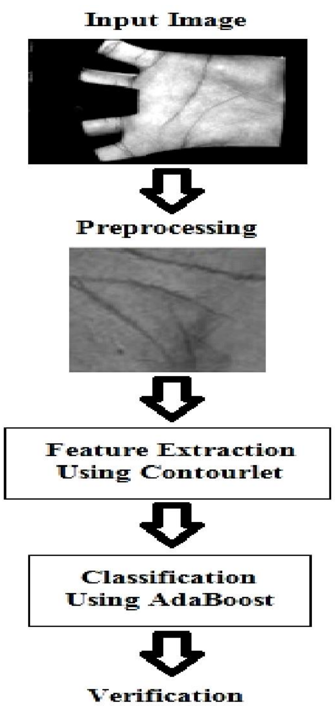

Figure 2. The flow chart of proposed palmprint verification system

The main steps of palmprint verification system are described below:

(1) Input Palmprint Image: We obtain a good quality palmprint image in a short time interval, that is captured by palmprint scanner and then the AC signal is converted into a digital signal, which is transmitted to a computer for further processing. Palmprint images in this case are from the Hong Kong Polytechnic University Palmprint Database [17].

(2) Preprocessing: Determine the two key points between fingers to establish a coordinate system for aligning different palmprint images. A coordinate system is set up on basis of the boundaries of fingers so as to extract a central part of a palmprint for feature extraction.

(3) Feature Extraction: We apply a contourlet transform to extract feature information from the central part.

(4) Classification: The AdaBoost classifier is used to classify palmprint features; hence the selected features are input to the related AdaBoost (α-Type) for classification.

In the palmprint verification mode, the user is asked to provide his/her user ID and his/her palmprint sample. Then the palmprint sample passes through preprocessing and feature extraction.

The extracted features are compared with templates in the database belonging to the same user ID. The rest of this paper is organized as the follows: Palmprint image preprocessing steps are mentioned in Section 2. Palmprint feature extraction using Contourlet transform is explained in Section 3. Classification using AdaBoost classifier described in Section 4. Section 5 is dedicated to Palmprint Verification Using the Contourlet Transform and AdaBoost Algorithm. Experimental results are given in Section 6. Finally, we present our conclusions in Section 7.

2. Palmprint image preprocessing

Preprocessing is important for the segmentation of region of interest (ROI) and feature extraction, it is necessary to obtain a sub-image from the captured palmprint image and to eliminate the variations caused by rotation and translation.

Hence palmprint images should be orientated and normalized before feature extraction and matching [6]. In this project work we have not taken any palmprint scanner for acquisition of palmprint images. Rather we have used the online database of Hong Kong Polytechnic University Palmprint Database [17].

The six main steps of palmprint image preprocessing are as follows (see Figure 3):

Step1. Apply a low-pass filter, such as Gaussian to the original image (see Figure 3 (a)) and use a threshold to convert it to a binary image (see Figure 3 (b)).

Step2. Extract the palm's boundary (see Figure 3(c)).

Step3. Use straight lines (L^1 and L^2, L^3 and L^4) to fit the segments of the boundary of the first finger, middle finger, third finger and little finger (see Figure 3 (d)):

$$L^i : y = k_i x + b_i \tag{1}$$

Where k_i and b_i are the slope and intercept of L^i (i=1, 2, 3, 4), which can be computed by the following equations:

$$k_i = \frac{\sum_{k=1}^{M_i} x_i^k \times \sum_{k=1}^{M_i} y_i^k - M_i \times \sum_{k=1}^{M_i} \left(x_i^k \times y_i^k\right)}{\left(\sum_{k=1}^{M_i} x_i^k\right)^2 - M_i \times \sum_{k=1}^{M_i} \left(x_i^k\right)^2} \qquad (2)$$

$$b_i = \frac{\sum_{k=1}^{M_i} y_i^k - k_i \times \sum_{k=1}^{M_i} x_i^k}{M_i} \qquad (3)$$

where $\left\{\left(x_i^k, y_i^k\right)\right\}_{k=1}^{M_i}$, (i=1, 2, 3, 4) are the coordinates of the points on the segments of the boundary of the first finger, middle finger, third finger and little finger, respectively; M_i is the total number of the points on the corresponding segment.

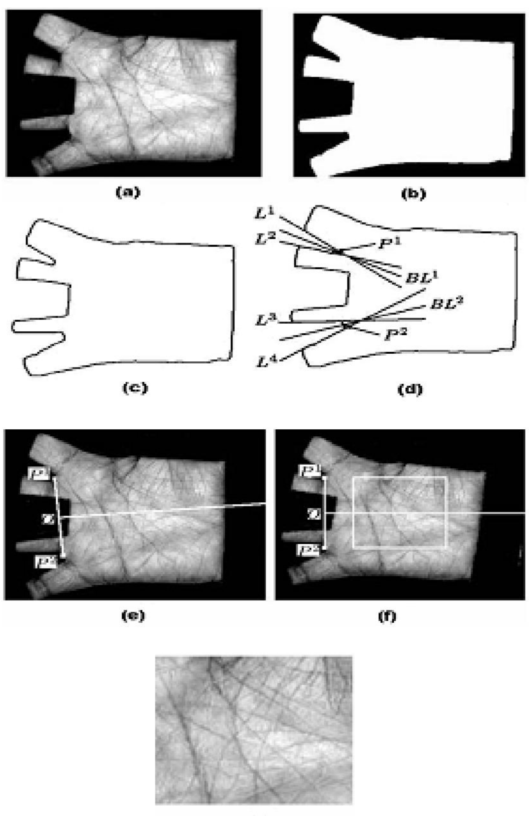

Figure 3. Main steps of preprocessing (a) Original image (b) Binary image (c) Boundary tracking (d) Line fitting, bisectors (e) Palmprint coordinate system (f) Central part extraction (g) Preprocessed result

Step4. Computing the bisectors (BL^1 and BL^2) of the angles formed by L^1 and L^2, L^3 and L^4 :

$$BL^i : y = K_i x + B_i \qquad (4)$$

Where K_i and B_i are the slope and intercept of BL^i (i=1, 2), which can be computed by the following equations:

$$K_i = \frac{k_{2\times i-1} \times \sqrt{1+k_{2\times i}^2} + k_{2\times i} \times \sqrt{1+k_{2\times i-1}^2}}{\sqrt{1+k_{2\times i-1}^2} + \sqrt{1+k_{2\times i}^2}} \qquad (5)$$

$$B_i = \frac{b_{2\times i-1} \times \sqrt{1+k_{2\times i}^2} + b_{2\times i} \times \sqrt{1+k_{2\times i-1}^2}}{\sqrt{1+k_{2\times i-1}^2} + \sqrt{1+k_{2\times i}^2}} \qquad (6)$$

Where $i = 1,\ 2$; $k_1 \sim k_4$, $b_1 \sim b_4$ are computed by (2) and (3). The intersection of BL^1 and the boundary, BL^2 and the boundary are P^1 and P^2, respectively (see Figure 3 (d)).

Step5. Line up point P^1 and P^2, and make a palmprint coordinate system in which y-axis is line P^1P^2 and the original point is the midpoint of line segment P^1P^2 (see Figure 3(e) and 3(f)).

Step6.Extracting a sub-image with fixed size from the center of the image (see Figure 3 (g)).

3. Palmprint feature extraction using Contourlet transform

The limitations of commonly used separable extensions of one-dimensional transforms, such as the Fourier and wavelet transforms, in capturing the geometry of image edges are well known [18].

The contourlet transform is a new extension to the wavelet transform in two dimensions using non-separable and directional filter banks [20, 23, 29]. The contourlet transform uses contour segments and fine details in images to realize the local, multi-resolutional and directional image expansion [19, 21, 22, 26]. Contourlet is implemented by the Pyramidal Directional Filter Banks (PDFB) that is a cascade of a Laplacian Pyramid (LP) and Directional Filter Banks (DFB) [22, 23, 24]. With this rich set of basis functions, the contourlet transform effectively capture smooth contours that are the dominant feature in natural images. In contourlet transform, the Laplacian pyramid does the decomposition of images into sub-bands and then the directional filter banks analyze each detail image as illustrated in Figure 4.

Figure 4 shows a flow graph of the contourlet transform [19, 21, 28]. It consists of two major stages: the sub-band decomposition and the directional transform. At the first stage, we used Laplacian pyramid (LP), and for the second stage, we used directional filter banks (DFB) [28].

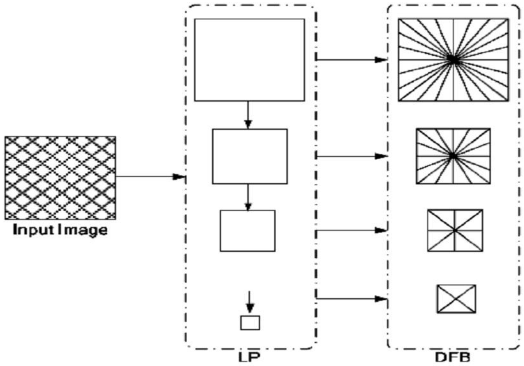

Figure 4. A flow graph of the Contourlet Transform

The pyramidal directional filter bank (PDFB), was proposed by Minh Do and Vetterli, which overcomes the block-based approach of curvelet transform by a directional filter bank, applied on the whole scale also known as contourlet transform (CT) [18, 20, 25].

The grouping of wavelet coefficients suggests that one can obtain a sparse image expansion by first applying a multi-scale transform and then applying a local directional transform to gather the nearby basis functions at the same scale into linear structures. In essence, first a wavelet-like transform is used for edge (points) detection, and then a local directional transform for contour segments detection. With this insight, one can construct a double filter bank structure (Figure 5 (a)) in which at first the Laplacian pyramid (LP) is used to capture the point discontinuities, and followed by a directional filter bank (DFB) to link point discontinuities into linear structures [18, 19, 26, 29].

The overall result is an image expansion with basis images as contour segments, and thus it is named the contourlet transform. The combination of this double filter bank is named pyramidal directional filter bank (PDFB).

Figure 5 (a) shows the block diagram of a PDFB. First a standard multi-scale decomposition into octave bands is computed, where the low pass channel is sub-sampled while the high pass is not.

Then a directional decomposition with a DFB is applied to each high pass channel. Figure 5 (b) shows the support shapes for contourlets implemented by a PDFB that satisfies the anisotropy scaling relation [18, 19, 27].

From the upper line to the lower line, four reduces the scale while the number of directions is doubled. PDFB allows for different number of directions at each scale/resolution to nearly achieve critical sampling. As DFB is designed to capture high frequency components (representing directionality), the LP part of the PDFB permits sub-band decomposition to avoid "leaking" of low frequencies into several directional sub-bands, thus directional information can be captured efficiently.

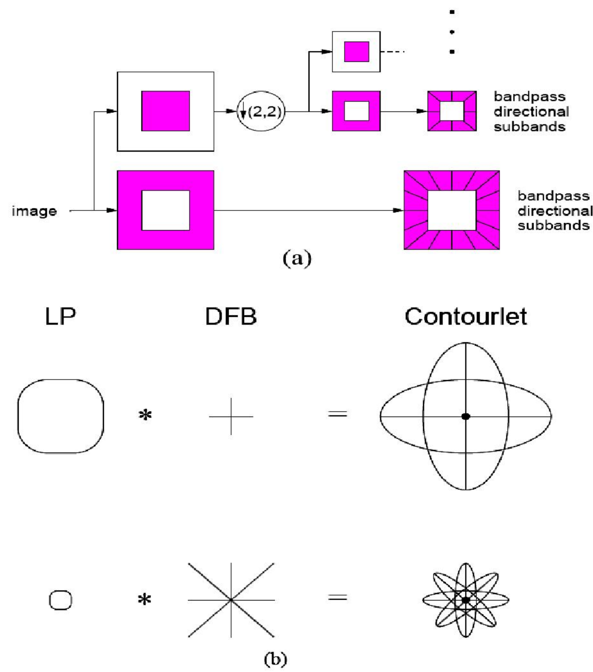

Figure 5. (a) Block diagram of a PDFB, (b) Supports for Contourlets

For the contourlet transform to satisfy the anisotropy scaling relation, one simply needs to impose that in the PDFB, the number of directions is doubled at every other finer scale of the pyramid. Figure 5 (b) graphically depicts the supports of the basis functions generated by such a PDFB. As can be seen from the two shown pyramidal levels, the support size of the LP is reduced by four times while the number of directions of the DFB is doubled. Combine these two steps, the support size of the PDFB basis functions are changed from one level to next in accordance with the curve scaling relation. In this contourlet scheme, each generation doubles the spatial resolution as well as the angular resolution. The PDFB provides a frame expansion for images with frame elements like contour segments, and thus is also called the contourlet transform.

3.1 Laplacian Pyramid

One way of achieving a multi-scale decomposition is to use a Laplacian pyramid (LP), introduced by Burt and Adelson. The LP decomposition at each level generates a down sampled low pass version of the original and the difference between the original and the prediction, resulting in a band-pass image as shown in Figure 6 (a). In this figure [18, 19, 30], 'H' and 'G' are called analysis and synthesis filters and 'M' is the sampling matrix. The process can be iterated on the coarse version.

In Figure 6 (a) the outputs are a coarse approximation 'a' and a difference 'b' between the original signal and the prediction. The process can be iterated by decomposing the coarse version repeatedly. The original image is convolved with a Gaussian kernel [18, 19].

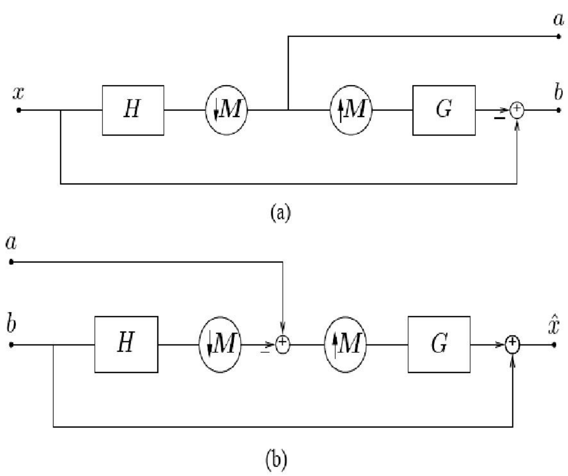

Figure 6. Laplacian pyramid scheme (a) analysis, (b) reconstruction

The resulting image is a low pass filtered version of the original image. The Laplacian is then computed as the difference between the original image and the low pass filtered image. This process is continued to obtain a set of band-pass filtered images (since each one is the difference between two levels of the Gaussian pyramid).

In this case, we proposed the use of the optimal linear reconstruction using the dual frame operator (or pseudo-inverse) as shown in Figure 6 (b).

The new reconstruction differs from the usual method, where the signal is obtained by simply adding back the difference to the prediction from the coarse signal, and was shown to achieve significant improvement over the usual reconstruction in the presence of noise [18].

Thus the Laplacian pyramid is a set of band pass filters. By repeating these steps several times a sequence of images, are obtained. If these images are stacked one above another, the result is a tapering pyramid data structure, as shown in Figure 7 and hence the name [19].

The Laplacian pyramid can thus be used to represent images as a series of band-pass filtered images, each sampled at successively sparser densities. It is frequently used in image processing and pattern recognition tasks because of its ease of computation. A drawback of the LP is the implicit oversampling. However, in contrast to the critically sampled wavelet scheme, the LP has the distinguishing feature that each pyramid level generates only one band- pass image (even for multi-dimensional cases), which does not have "scrambled" frequencies.

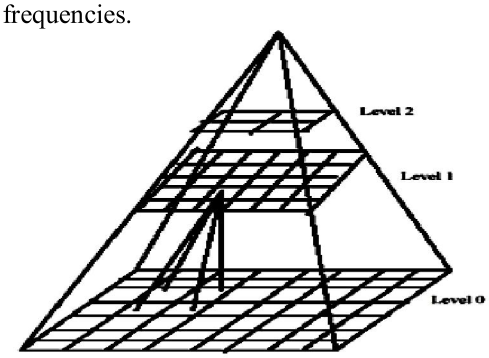

Figure 7. Laplacian pyramid structure

This frequency scrambling happens in the wavelet filter bank when a high pass channel, after down sampling, is folded back into the low frequency band, and thus its spectrum is reflected. In the LP, this effect is avoided by down sampling the low pass channel only.

3.2 Directional Filter Bank

In 1992, Bamberger and Smith introduced a 2-D directional filter bank (DFB) that can be maximally decimated while achieving perfect reconstruction [18, 19]. The directional filter bank is a critically sampled filter bank that can decompose images into any power of two's number of directions.

The DFB is efficiently implemented via a l-level tree-structured decomposition that leads to '2l' sub-bands with wedge-shaped frequency partition as shown in Figure 8 [18, 19, 25, 30].

The original construction of the DFB involves modulating the input signal and using diamond-shaped filters. Furthermore, to obtain the desired frequency partition, an involved tree expanding rule has to be followed. As a result, the frequency regions for the resulting sub-bands do not follow a simple ordering as shown in Figure 7 based on the channel indices. The DFB is designed to capture the high frequency components (representing directionality) of images. Therefore, low frequency components are handled poorly by the DFB. In fact, with the frequency partition shown in Figure 8, low frequencies would leak into several directional sub-bands, hence DFB does not provide a sparse representation for images.

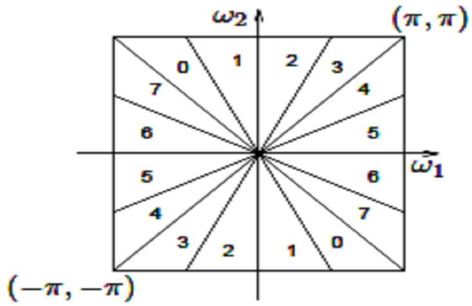

Figure 8. DFB frequency partitioning

To improve the situation, low frequencies should be removed before the DFB. This provides another reason to combine the DFB with a multi-resolution scheme. Therefore, the LP permits further sub-band decomposition to be applied on its band-pass images.

Those band-pass images can be fed into a DFB so that directional information can be captured efficiently. The scheme can be iterated repeatedly on the coarse image. The end result is a double iterated filter bank structure, named pyramidal directional filter bank (PDFB), which decomposes images into directional sub-bands at multiple scales. The scheme is flexible since it allows for a different number of directions at each scale. Figure 9 shows the contourlet transformation coefficients of palmprint image without preprocessing step. Each image is decomposed into a low pass sub-band and several band-pass directional sub-bands. It can be seen that only contourlets that match with both location and direction of image contours produce significant coefficients. Thus, the contourlet transform effectively explores the fact, that the edges in images are localized in both location and direction.

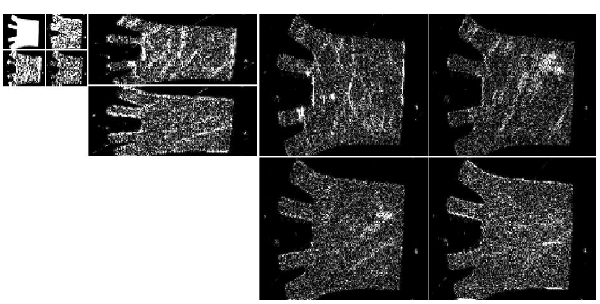

Figure 9. Contourlet transform of palmprint image without preprocessing step

One can decompose each scale into any arbitrary power of two's number of directions, and different scales can be decomposed into different numbers of directions. This feature makes contourlets a unique transform that can achieve a high level of flexibility in decomposition while being close to critically sampled. Other multi-scale directional transforms either have a fixed number of directions or are significantly over complete.

4. Classification using AdaBoost classifier

"Boosting" is a general method for improving the performance of any weak learning algorithm that consistently generates classifiers which need to perform only slightly better than random guessing.

A recently proposed and very promising boosting algorithm is AdaBoost.

It has been applied with great success to several benchmark machine learning problems using rather simple learning algorithms, in particular decision trees. AdaBoost is a boosting algorithm, running a given weak learner several times on slightly altered training data, and combining the hypotheses to one final hypothesis, in order to achieve higher accuracy than the weak learner's hypothesis would have.

The main idea of AdaBoost is to assign each example of the given training set a weight. At the beginning all weights are equal, but in every round the weak learner returns a hypothesis, and the weights of all examples classified wrong by that hypothesis are increased.

That way, the weak learner is forced to focus on the difficult examples of the training set. The final hypothesis is a combination of the hypotheses of all rounds, namely a weighted majority vote, where hypotheses with lower classification error have higher weight. In this section the two versions of AdaBoost are described although the more theoretical properties are explained.

The two versions are identical for binary classification problems and differ only in their handling of problems with more than two classes. We use the original notation used by Schapire rather than the more convenient notation of the recent generalization of AdaBoost by Schapire and Singer [31, 32].

Basic α-Type AdaBoost algorithm can be presented as follow:

- Initialize distribution over the training set $D_i = 1/m$
- For t = 1…T:
- Train Weak Learner using distribution D_t.
- Choose a weight (or confidence value) $\alpha_t \in R$.
- Update the distribution over the training set:

$$D_{t+1} = \frac{D_t(i)e^{-\alpha_t y_i h_t(x_i)}}{Z_t} \qquad (7)$$

We should choose α_t to minimize Z_t (normalization factor). It has been shown that α can be found analytically as follows:

$$\alpha = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right) \tag{8}$$

Where:

$$r = \sum_i D_i u_i \quad , \quad r \in [-1,1] \tag{9}$$

$$u_i = y_i \,.\, h(x_i) \tag{10}$$

$$Z = Z_t,\ \ D = D_t,\ \ h = h_t,\ \ \alpha = \alpha_t \tag{11}$$

And y_i is the target output, u_i is positive if hypothesis $h(x_i)$ is correct, and negative if it is incorrect. In this section, we present pseudo-code for the two versions of β-type AdaBoost algorithm (Basic β-Type AdaBoost algorithm and multi-class extension using confidence scores) in Table 1.

Table 1. Basic β-Type AdaBoost algorithm (left), Multi-class extension using confidence scores (right)

Input: sequence of N examples $(x_1, y_1), \ldots, (x_N, y_N)$ with labels $y_i \in Y = \{1, \ldots, k\}$	
Init: $D_1(i) = 1/N$ for all i	**Init:** let $B = \{(i,y): i \in \{1,\ldots,N\}, y \neq y_i\}$ $D_1(i,y) = 1/\lvert B\rvert$ for all $(i,y) \in B$
Repeat: 1. Train neural network with respect to distribution D_t and obtain hypothesis $h_t : X \to Y$ 2. calculate the weighted error of h_t: $\epsilon_t = \sum_{i:h_t(x_i)\neq y_i} D_t(i)$ abort loop if $\epsilon_t > \frac{1}{2}$ 3. set $\beta_t = \epsilon_t/(1-\epsilon_t)$ 4. update distribution D_t $D_{t+1}(i) = \frac{D_t(i)}{Z_t}\beta_t^{\delta_i}$ with $\delta_i = (h_t(x_i) = y_i)$ and Z_t a normalization constant	**Repeat:** 1. Train neural network with respect to distribution D_t and obtain hypothesis $h_t : X \times Y \to [0,1]$ 2. calculate the pseudo-loss of h_t: $\epsilon_t = \frac{1}{2}\sum_{(i,y)\in B} D_t(i,y)(1-h_t(x_i,y_i)+h_t(x_i,y))$ 3. set $\beta_t = \epsilon_t/(1-\epsilon_t)$ 4. update distribution D_t $D_{t+1}(i) = \frac{D_t(i)}{Z_t}\beta_t^{\frac{1}{2}((1+h_t(x_i,y_i)-h_t(x_i,y))}$ where Z_t is a normalization constant
Output: final hypothesis: $f(x) = \arg\max_{y\in Y} \sum_{t:h_t(x)=y} \log\frac{1}{\beta_t}$	**Output:** final hypothesis: $f(x) = \arg\max_{y\in Y} \sum_t \left(\log\frac{1}{\beta_t}\right) h_t(x,y)$

5. Palmprint Verification Using the Contourlet Transform and AdaBoost Algorithm

The wavelet transform is well adapted to point singularities, so it has a problem with orientation selectivity. This is an important drawback for wavelet-based feature extraction in invariant palmprint classification. The contourlet transform was recently developed by Do and Vetterli [18] to overcome the limitations of wavelets. It is based on an efficient two dimensional multi-scale and directional filter bank that can deal effectively with images having smooth contours.

It uses a combination of a Laplacian Pyramid (LP) that decomposes an image into a number of radial sub-bands, and a Directional Filter Bank (DFB), where each LP detail sub-band is fed to this stage to be decomposed into a number of directional sub-bands. Contourlets have elongated supports at various scales, directions, and aspect ratios. Therefore, they are good at capturing directional features in the palm-prints in a multiresolutional way.

Since the contourlet transform has very desirable properties for invariant palmprint recognition, we will use it to extract features to recognize the unknown palmprint images. The original palm samples contain the fingers and the background. This is undesirable. We extract the central portion of the palm sample and save it to a matrix of size 128 × 128 for later processing. We apply the contourlet transform to the extracted palmprint image for a number of decomposition levels. After that, we use these extracted features for classification by AdaBoost (α-Type).

The steps of our proposed method for palmprint verification can be summarized as follows:

1) Extract the central portion of the palm sample image by preprocessing module.

2) Perform the contourlet transform on the extracted palmprint image and extract features.

3) Classify the extracted features using AdaBoost (α-Type) classifier.

AdaBoost is a very popular boosting algorithm. It assigns each sample of the given training set a weight. All weights are initially set equal, but in every round the weak learner returns a hypothesis, and the weights of all examples classified wrong by that hypothesis are increased. Therefore, the weak learner will focus on the difficult samples in the training set. The final hypothesis is a combination of the hypotheses of all rounds and hypotheses with lower classification error have higher weight. In our experiments we find that our proposed algorithm achieves state-of-the-art palmprint classification rate, and it is very competitive.

The advantages of the proposed algorithm can be summarized as follows: The Contourlet transform has elongated supports at various scales, directions, and aspect ratios, and it is good at capturing directional features in the palm-prints in a multiresolutional way. The AdaBoost algorithm is a very effective method to classify unknown palmprint images. All these good properties combine in our new method, making it a very promising method for invariant palmprint verification. Experimental results confirm the feasibility of our proposed method for palmprint verification.

6. Experimental results

In order to test our proposed method for palmprint verification, we conduct experiments on the PolyU Palmprint Database [17].

Our experiments are programmed and tested by using Matlab software on a data set formed from 240 samples, i.e. The database contains 40 different palms, and each has six samples palmprint image. For each palm, we use five of the six palmprint samples for training and the one palmprint sample for testing. The size of the original palms without preprocessing is of 284 × 384 pixels. We extract the central portion of the palm image for palmprint verification.

The extracted palmprint image by preprocessing module has a size of 128 × 128 pixels. Five decomposition levels of the contourlet transform are applied to the extracted palmprint image. 16 feature vectors extracted are final features that used for AdaBoost for feature classification. We used leave-one-out technique to obtain statistically validated results from neural networks and AdaBoost, during training and test phases.

We measured the global performance of the systems using the three following indices:

False Acceptance Rate (FAR), False Rejection Rate (FRR) and total percent of miss classifications (Error).

For all of the inputs weak learner case, we have tested a system implemented using α-Type AdaBoost with different number of iterations (T).

In our system, neural networks have been used as weak learners in AdaBoost. In order to meet the requirement of a weak learner, we selected the simplest structure of a typical neural network, i.e. a simple neuron.

Consequently, each weak learner had one output whose the value determined the weak learner's vote concerning the identity of an individual.

Since the hyperbolic tangent was used as the neurons activation function, a positive output indicated a positive verification result and a negative output indicated a negative verification result. Nguyen-Widrow weights initialization, Levenberg-Marquardt back-propagation learning algorithm and Mean Square Error (MSE) criteria were used in neural networks training phases.

We mention again that each of the curve points in Figure 10 were obtained by averaging the results of several leave-one-outs experiments.

Figure 10 shows that the error rates converge, after only ten iterations, to the following values:

- FAR= % 0.2137,
- FRR= % 5.8333 and
- ERROR= % 0.3021

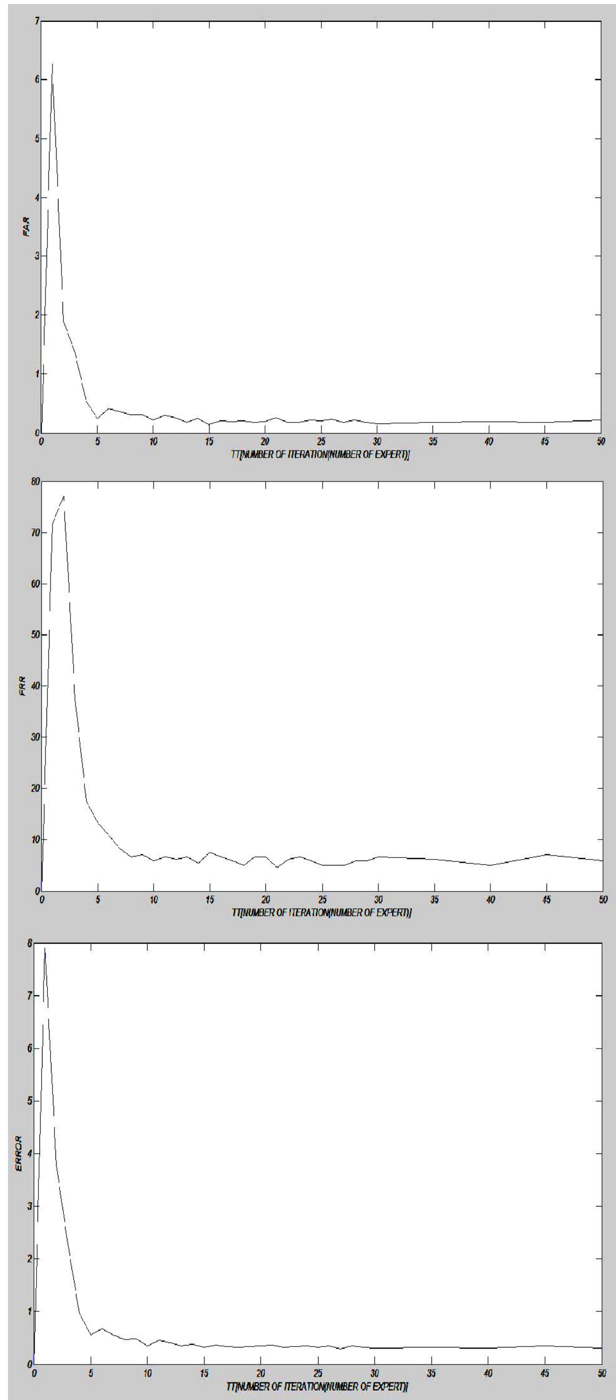

Figure 10. System performance indices obtained with different number of iterations. FAR (above), FRR (middle) and Error (below) converges after about ten iterations for α-Type AdaBoost

7. Conclusions

In this paper, we propose a new method for palmprint verification by using the contourlet features and AdaBoost. The contourlet transform has the multi-scale and time-frequency localization properties of wavelets, but also offers a high degree of directionality and anisotropy. These properties are very important in palmprint verification.

The AdaBoost (α-Type) is also used as a classifier for palmprint verification. Obviously, the main goal was to optimize the system design with respect to the verification error and computational cost.

In order to minimize the computational cost, according to the AdaBoost condition for weak learners, we selected a very simple expert as weak learner, i.e. a single neuron. Also, based on our experiments, we showed that using an AdaBoost (α-type) structure with full input weak learner's connections (16 inputs or feature vectors), we obtained a FAR as low as % 0.2137 and FRR as low as % 5.8333 with only ten iterations.

Focusing our attention on FAR, which plays a very important role in secure environments; we showed that even the average FAR and the average FRR are acceptable.

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