Personal Authentication Using Palm Print Features*

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Abstract

Biometrics-based authentication is a verification approach using the biological features inherent to each individual. They are processed based on the identical, portable, and arduous duplicate characteristics. In this paper, we propose a scanner-based personal authentication system by using the palmprint features. The authentication system consists of enrollment and verification stages. In the enrollment stage, the training samples are collected and processed to generate the matching templates. In the verification stage, a query sample is matched with the reference templates to decide whether it is a genuine sample or not. The region of interest(ROI) for each sample is first generated to obtain the palmprint features by using Sobel and morphological operations. We use the template matching and the backpropagation neural network to measure the similarity in the verification stage. Experimental results verify the validity of our proposed approaches in personal authentication.

1 Introduction

Recently, biometric features have been widely used in many personal authentication applications because they possess the following physiological properties[1]: *universality, uniqueness, permanence, collectablilty, performance, acceptability,* and *circumvention.* Biometrics features are the features extracted from human biological organs or behavior. O'Gorman[2] also surveyed six biometric features in the matching, validation, maximum independent samples per person, sensor cost, and sensor size topics. Though fingerprint and eye features provide very high recognition rate, they are unsuitable for identification systems. First, the sensor cost of eye-based features is too high to implement in many low security demanding applications such as computer, home security systems, restricted entry control, corporate networks, etc. Besides, since fingerprint features are used officially in criminal investigations and commercial transactions, most of the users are unwilling to deliver their fingerprint data to a company or system for privacy reason. In this paper, we propose a palmprint-based technology to identify the individuals in the entry control systems.

In many lectures, two possible biometric features can be extracted from human hands. First, hand shape geometrical features such as finger width, length, and thickness are the well-known features adopted in many systems. These features frequently vary due to the wearing of rings in fingers. According to the variation of hand geometry, it can be used in the entry control systems with low security requirements and a low rejection rate to record the entry data of employees or users. Besides, the reference features in the database should be updated frequently. Comparing with the palm shape features, the relatively stable features extracted from the hands is the print of palms.

Golfarelli *et al.*[3] extracted 17 hand shape features to verify the personal identity. Joshi *et al.*[4] captured an image of middle finger by using a CCD camera to generate the wide line integrated profile(WLIP) of length 472. Zunkel[5] introduced a commercial product of hand geometry-based recognition and applied it to many access control systems. Jain *et al.*[6] used the deformable matching techniques to verify the individuals via the hand shapes. 96.5% accuracy rate and 2% false acceptance rate(FAR) are achieved by their approaches. Zhang and Shu[7] applied the datum point invariant property and the line feature matching technique to conduct the verification process via the palmprint features extracted from the inked papaer. It is not suitable for many on-line security systems because

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two steps are needed to obtain the palm-print images in their approach.

In this paper, we propose a scanner-based personal authentication system by using the palm print features. Two stages, *enrollment* and *verification* stages, constitute the identification system. In the enrollment stage, M hand images of an individual are collected to be the training samples. These samples should be processed by the *pre-processing*, *feature extraction*, and *modeling* modules to generate the matching templates. In the verification stage, a query sample is also processed by the preprocessing and feature extraction modules, and then be matched with the templates to decide whether it is a genuine sample or not. In our proposed palmprint-based identification system, the preprocessing module, including *image thresholding*, *board tracing*, *wavelet-based segmentation*, and *ROI location* steps, should be performed to obtain a square region in a palm table which is called region of interest(ROI). Then, we perform the feature extraction process to obtain the feature vectors by the Sobel and morphological operations. The reference templates for a specific user are generated in the modeling module. In the verification stage, we use the template matching and backpropagation neural network to measure the similarity between the reference templates and test samples.

The rest of this paper is organized as follows. In Section 2, four steps for the pre-processing module are executed to find the location of ROI. The feature extraction techniques, including Sobel's and morphological operations are described in Section 3. The modeling procedure for the verification purpose is introduced in Section 4. First, the simple and practical multiple template matching method is designed in the section to evaluate the similarity between the query and reference samples. The BP-based NN is also built in Section 4 to compute the similarity values for verification . In Section 5, experimental results are demonstrated to verify the validity of our proposed algorithms. Finally, some concluding remarks are given in Section 6.

2 Preprocessing

In the preprocessing module, four steps are devised to obtain a square region which possesses the palmprint data. In the following contexts, we will present the details of these four steps.

Step 1: Image Thresholding

The hand images of 256 gray levels are acquired from a platform scanner as shown in Fig. 1. The image thresholding operation is to binarize the gray images to obtain the binary hand shape images. In this step, the histogram of gray images are analyzed to determine a threshold value. This value is automatically set at the local minimal value between 50 and 100.

Step 2: Border Tracing

After the image thresholding step, the binary images are traced to obtain the contours of hand shape by making use of the border tracing algorithm[8]. The main purpose of this step is to find the boundary of a hand image and then locate the positions of five fingers for the determination of region of interest(ROI). At the beginning, the first point of hand shape is set at the upper-left point of a hand shape image. The contour of hand shape is then traced in counterclockwise direction. The coordinates of each traced pixel should be kept to represent the shape of hand.

Step 3: Wavelet-based Segmentation

In this step, the wavelet-based segmentation technique is adopted to find the locations of five finger tips and four finger roots. As we know, these points are located at the corner of hand shape. The coordinates of border pixels are transformed into the profile of curvature as depicted in Fig. 2(a). The profile of curvature is then transformed to multi-resolutional signals of low-frequency and high-frequency sub-bands. Since the crucial points P_a, P_b, and P_3 of corner points(See Fig. 3(a)) determine the ROI location in the palm table, it is very important to explicitly locate the corner points of hand shape. The wavelet transform can provide stable and effective segmented results in corner detection. From these signals, the corner are labeled at the local minimal points of negative magnitude which can be located between two zero-crossing points.

Step 4: Region of Interest(ROI) Generation

In this step, we will find the region of interest (abbreviated as ROI) in the palm table as shown in Fig. 3 which is the operating region both in the enrollment and verification processes. According to the result generated in Step 3, the location of ROI is determined from points P_a, P_b, P_e, and geometrical formula. Here, assume the unit vector of points P_a and P_b to be $\vec{ab} = (\vec{a}, \vec{b})$ and $P_o = (x_o, y_o) = ((x_a + x_b)/2, (y_a + y_b)/2)$, $|P_aP_b|$ is the length of points P_a and P_b. The location of extened point P_e is calculated as $(x_e, y_e) = (x_o, y_o) + |P_aP_b|(\vec{b}, -\vec{a})$. The square region $P_{e_1}P_{e_2}P_{e_3}P_{e_4}$ is generated as follows:

$$(x_{e_1}, y_{e_1}) = (x_e, y_e) + 128 * (\vec{a}, \vec{b})$$

$$
\begin{aligned}
(x_{e_2}, y_{e_2}) &= (x_e, y_e) - 128 * (\vec{a}, \vec{b}) \\
(x_{e_3}, y_{e_3}) &= (x_{e_2}, y_{e_2}) + 256 * (\vec{b}, -\vec{a}) \\
(x_{e_4}, y_{e_4}) &= (x_{e_1}, y_{e_1}) + 256 * (\vec{b}, -\vec{a})
\end{aligned}
$$

3 Feature Extraction

Feature extraction is a step to extract the meaningful features from the segmented ROI for the later modeling or verification process. In extracting the features, we use the operator-based approach to extract the line-like features of palmprint in the ROI of palm table.

First, we employ the simple Sobel operators to extract the feature points of palmprint. Four directional Sobel operators S_0, S_{90}, S_{45}, and S_{135} are designed. Consider a pixel of ROI in the palm table, four directional Sobel operators are performed to select the maximal value as the resultant value of ROI. This operation is operated according to the following expression:

$$f * S = \max\left(f * S_0, f * S_{45}, f * S_{90}, f * S_{135}\right). \quad (1)$$

Here, symbol $*$ is defined as the convolution operation. The Sobel's features of ROI are thus obtained.

Next, we present another complex morphological operators to extract the palmprint features. In the gray-scale morphology theory, two basic operations *dilation*($\oplus$) and *erosion*($\ominus$) for image f are defined. In addition, two combination operations called *operation*($\circ$) and *closing*($\bullet$) are extended for the further image processing. In [9], Song and Mevro designed an edge detector called *alternating sequential filter*(ASF) which provides perfect effects in the noisy or blurry images. The mechanism of ASF is constructed as follows. Two filters are defined to be

$$f_1 = \gamma_l \phi_l, \text{ and } f_2 = f_1 \oplus b_{3\times3}. \quad (2)$$

The algebraic opening γ_l and closing ϕ_l are defined as

$$
\begin{aligned}
\gamma_l &= \max\left(f \circ b_{0,l}, f \circ b_{45,l}, f \circ b_{90,l}, f \circ b_{135,l}\right), \quad (3) \\
\phi_l &= \min\left(f \bullet b_{0,l}, f \bullet b_{45,l}, f \bullet b_{90,l}, f \bullet b_{135,l}\right),
\end{aligned}
$$

where symbols $b_{\alpha,l}$ denote the structuring elements of length l and angle α. In our experiments, value l is set to be 5. Next, the morphological operator is defined to be $f_m = f_2 - f_1$. The edge pixels are thus obtained by using the morphological function $f * f_m$.

Now, the feature vectors are created in the following way. Consider the training samples, the ROI images are uniformly divided into several small grids. The mean values of pixels in the grids are calculated to obtain the feature values. These values are sequentially arranged row by row to form the feature vectors. In our experiments, three different grid sizes 32×32, 16×16 and 8×8 are adopted to obtain the multi-resolutional feature vectors.

4 Enrollment and Verification Processes

In this section, we develop two methods, *multiple template matching* and *backpropagation*(BP) neural network-based approaches, to train the models for a palmprint-based authentication system.

4.1 Multi-template matching approach

Consider a query sample x and a template sample y, a *correlation* function is utilized to measure the similarity between two feature vectors as follows:

$$R_{xy} = 1 - \frac{\sum_{i=1}^{n}(x_i - \mu_x)(y_i - \mu_y)}{\sigma_x \sigma_y}. \quad (4)$$

In Eq. (4), symbols μ and σ represent the mean and standard derivation values, respectively. In addition, value n is the length of feature vectors which is set to be 32 by 32, 16 by 16, or 8 by 8 in our experiments. This coefficient value of linear correlation function is calculated for the similarity evaluation.

In creating the reference templates in the enrollment stage, M samples of individual X are collected to form the matching template database. The main advantage of this approach is that less training time is needed in the training the matching model. In the verification stage, the correlation coefficient of query and reference samples is calculated by making use of Eq. (4). Based on this criteria, it is easy to verify the input pattern by a pre-defined threshold value t. If the value R is smaller than threshold t, the owner of query sample is claimed to be individual X. Otherwise, the query sample is classified as a forged pattern.

In many biometric-based verification models, the selection of threshold value t is the most difficult step in the enrollment stage. It will affect the false acceptance rate(FAR) and false rejection rate(FRR). Basically, these two values are contradicted with each other. In this section, the *leave-one-out* cross validation methodology is applied to evaluate the FRR. Consider M template samples of an individual X(called *positive samples*), and N samples of another persons(called *negative samples*). Assume sample x is a pattern in the M templates. The average distance for sample x to the other $M-1$ templates is computed to be $d_x = \sum_{j=1}^{M-1}(R_{xj})/(M-1)$. Moreover, the distances for the other $M-1$ reference samples are also obtained. If d_x is larger than threshold value t_X, sample x is a forged pattern and the value E_1(the error number of FRR) should be increased by 1. Similarly, the average distance d_y of a negative sample y to M reference templates is also calculated as $d_y = \sum_{j=1}^{M}(R_{yj})/M$. The value E_2 of error number for the computation of FRR is added by 1 when the average distance d_y is smaller than the threshold t_X. The performance index $\mathcal{I}_x$ for individual X is thus defined as the summation of FAR plus FRR as follows:

$$\mathcal{I}_x = E_1/M + E_2/N. \tag{5}$$

Next, list all possible threshold values from 0 to 1, and depict the curves of FAR and FRR. The best value $t_X = 0.38$ with the minimal performance index is chosen to be the threshold value. This threshold value t_X will be used in later verification process for individual X.

4.2 Backpropagation neural network(BPNN) approach

In this section, we apply the BP neural networkapproach to perform the verification task. The architecture of our proposed network is designed to be a three layer-based network which includes an input, a hidden and an output layers as depicted in Fig. 4. There are 80, 40 and, 1 neurons in each layer, respectively.

Now, we focus our attention on the sample collection step. In this step, M image samples of a specific individual X called positive samples and N image samples of another K persons called negative samples are collected to train the BP neural network. In order to increase the verification performance, J artificial generating samples are created from the M positive samples by using the bootstrap algorithm. Consider the ROI of an image sample, we randomly shift it left or right and up or down by 0 to 5 pixels, and randomly rotate it by -5 to +5 degrees. In our experiments, both positive and negative samples are equally created for the simplification of training process. In order to generate the same number of positive and negative samples, JK positive samples are generated by duplicating J positive samples K times for individual X. On the other hand, JK negative samples are randomly selected from K persons. These $2JK$ samples are inputted to the network at each training epoch.

5 Experimental Results

In this section, some experimental results are demonstrated to verify the validity of our approach.

5.1 Experimental environment

In our experimental environment, a platform scanner is used to capture the hand images. Users are asked to put their right hands on the platform of scanner without any pegs. The hand images of size 845 by 829 are scanned in gray-scale format and in 100 dpi (dot per inch) resolution. 30 hand images of each individual are grabbed in three times within three weeks to construct the database. In the enrollment stage, the first 10 images are used to train the verification model. The other 20 images are tested by the trained verifier. In the following contexts, the experimental results verified by the template matching and BP neural network algorithms are reported.

5.2 Verification using template matching algorithm

In the first experiment, three kinds of window sizes 32x32, 16x16, and 8x8 are adopted to evaluate the performance of the template matching methodology. In each window, the mean value of pixels is computed and considered to be an element of vectors. The linear correlation function is used to calculate the similarity between the reference and test samples. Consider a person X, 10 samples are chosen to be the reference templates of verifier. These 10 positive samples of individual X and 490 negative samples of 49 persons are collected to compute the type I and type II errors. The results of false acceptance rate(FAR) and false rejection rate(FRR) by all possible threshold values ranging from 0 to 1 for various grid window sizes are calculated to find the best threshold values, respectively. The threshold value t_X for individual X is chosen by the selection rule as stated in the previous section. Thereby, the query samples are verified by the verifier of X and thresholded by the pre-selected value t_X. Experiments on 1000 positive samples and $20 \times 50 \times 49$ negative samples of 50 persons are conducted to evaluate the performance. The multiple template matching algorithm can achieve the accuracy rates all above 91% as tabulated in Table 1. In this table, both FAR and FRR values are below 9%.

5.3 Verification using backpropagation neural network(BPNN)

In this section, the backpropagation neural network architecture is adopted as shown in Fig. 4 to decide whether the query sample is a genuine or not. In this experiment, the network for a specific individual X was trained for the latter verification process. 10 positive samples of individual X and 490 negative samples of another 49 persons were all collected to train the BP neural network. In order to obtain the best verification performance, 10 artificially generating samples were generated from each training sample by using the bootstrap algorithm. In the training phase, both positive and negative samples were equally created. 4900 positive samples were generated by duplicating 100 positive samples of individual X 49 times. On the other hand, 4900 negative samples were generated from the hand images of 49 selected persons. These 9800 samples are inputted to the network at each training epoch. In the testing phase, the other 20 positive images of individual X are verified by the trained BP neural network to evaluate the FRR value. Besides, 20×49 negative samples are also tested to compute the FAR value. In this experiment, 50 persons were selected and tested by their corresponding neural networks. The experimental results are listed in Table 1, and the average accuracy rates are both above 98% for the Sobel's and morphological features. Besides, both FAR and FRR values are below 2%.

Table 1: Experimental results by using the template matching and the BP neural network.

Feature	Sobel features			
Error	S8x8	S16x16	S32x32	BPNN
FRR	7.8%	4.5%	4.9%	0.6%
FAR	5.9%	6.7%	6.4%	1.79%

(a)

Feature	Morphological features			
Error	M8x8	M16x16	M32x32	BPNN
FRR	5.5%	3.3%	5.2%	0.5%
FAR	6.2%	6.6%	8.7%	0.96%

(b)

6 Conclusions

In this paper, a novel approach is presented to authenticate individuals by using their palm print features. The hand images are captured from a scanner without any fixed peg. This mechanism is very suitable and comfortable for all users. Besides, we propose two verification mechanisms, one is the template matching method and another is neural network-based method, to verify the palmprint images. In the template matching method, the linear correlation function is adopted as the metric measurement. Using this method, we can achieve above 91% accuracy rate. In the neural network-based method, we use the backpropagation mechanism and the scaled conjugate gradient algorithm to build up a neural network-based verifier. Using this verifier, we can obtain above 98% accuracy rate. Experimental results reveal that our proposed approach is feasible and effective in personal authentication using palmprint features.

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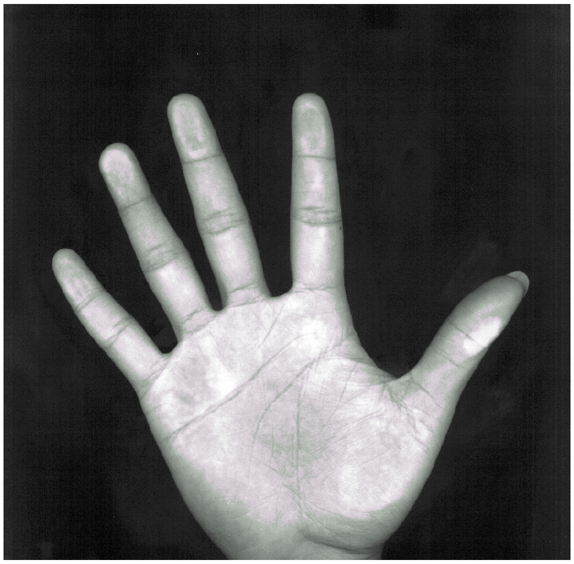


Figure 1: A hand image scanned in 100 dpi resolution.

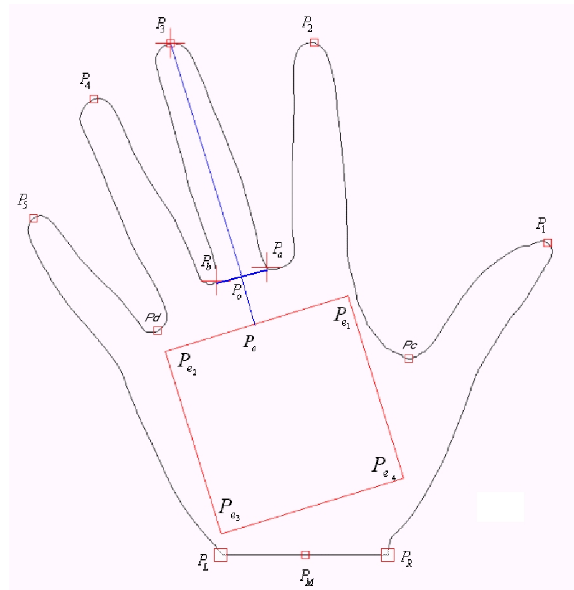
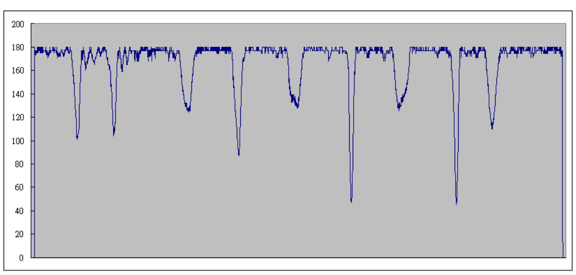
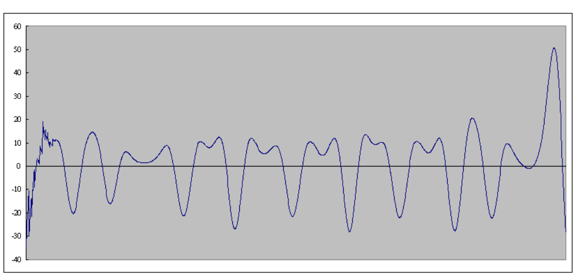


Figure 3: The generation of region of interest(ROI).



(a)



(b)

Figure 2: (a) The profile of curvature of hand shape, (b) the transformed profile of high-frequency sub-band.

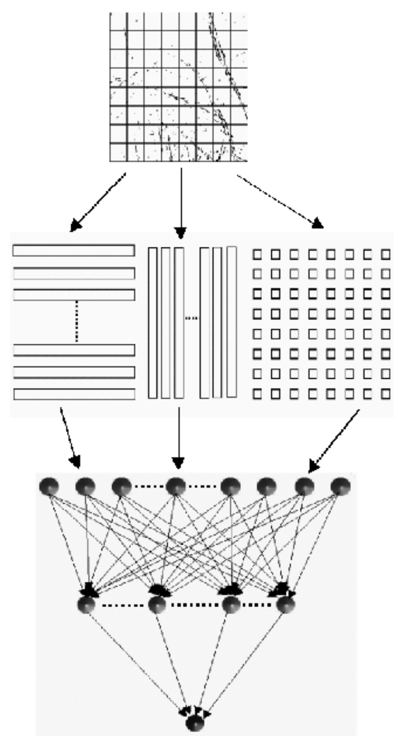


Figure 4: The mechanism of backpropagation neural network.