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An Efficient Hand Dorsal Vein Recognition Based on Neural Networks

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Abstract

This paper proposes an effective human hand vascular pattern recognition system by using multi-layered perceptron neural networks for biometric identification applications. Biometric hand dorsal vein images are acquired by using NIR (near infra-red) illuminated CCD camera from 103 persons of different ages and gender. The vascular region of interest (ROI) is cropped from hand images firstly and then mean filter and histogram equalization processes were applied to the 240x180 pixels resolution hand vein pattern images in order to restrain the noises. The gray-scaled vein pattern images were converted to the binary format by applying Otsu's thresholding method. The resulting images then are divided into 20x20 pixel dimensioned sub-images before feature extraction. Average absolute deviation (AAD) algorithm was implemented to these sub-images for getting the feature sets. Multi-layer perceptron neural network (MLPNN) method was performed for identification of the human hand vein pattern images. Experimental results showed that the proposed method achieved correct classification rates up to 100%

Keywords: Biometric identification; hand dorsal vein recognition; artificial neural networks

Introduction

Biometric identification techniques use behavioral and physiological characteristics for person authentication. Vein is the one of these physiological characteristics. The vein biometric identification system has attracted increasing attention in recent years because of some advantages. First of all, the vascular structure is unique since identical twins have different vein patterns. The veins are found inside the human body and stable in time, so they are not easily damaged or don't change. Besides that, the vascular patterns are hard to be copied or captured by the intruders compared to other biometric traits.

The usage of the hand features for biometric purposes is based on old times. The first systematic capture of handprint for the aim of identification of the workers is recorded in India in 1858 (Biometrics History 2006). There are three approaches in hand vein biometric authentication applications. These are; finger vein identification that uses vascular pattern inside the finger, hand palm vein identification that uses the vascular

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pattern in front side of the hand and hand dorsal vein identification that uses the vascular pattern in back side of the hand. In the proposed system, we used hand dorsal vein structure for biometric identification.

This paper is organized as follows. In section 2, previous works on biometric identification system based on hand dorsal vein patterns are introduced. The implementation of hand dorsal vein identification system is presented in section 3. This section has image acquisition, pre-processing, feature extraction and MLPNN based classification. The experimental results are analyzed in section 4. Concluding remarks are given in the last section of this work.

Literature Overview

The first biometric identification system based on vascular structure called "VeinCheck" was presented by Mac Gregor and Welford in 1991 (MacGregor and Welford 1991). The previous studies were discussed in accordance with only hand dorsal vein pattern recognition researches in this section. Mehnert et al. was reported a research about segmentation of the subcutaneous vascular network of the back of the hand in 1993 (Mehnert et al. 1993). Im et al. was made a study on DSP based vein pattern recognition system and suggested conventional preprocessing algorithm (Im et al. 2001). Another work on filter bank based hand vascular pattern identification was presented by Im and Choi in 2002 (Im and Choi 2002). In 2003, Im et al. was suggested a direction-based algorithm for feature extraction of the hand vascular patterns (Im et al. 2003). Lin was made a research thesis on biometric verification using palmprints and vein patterns of palm dorsum in 2004 in Institute of Computer Science and Information Engineering at Na-tional University, Taiwan (Lin 204). In 2005, Ding et al. was proposed a new segmentation method and improved conditional thinning method for hand vein recognition (Ding et al. 2005). Wang and Leedham were presented thermal-imaged vein pattern based personal verification system (Wang and Leedham 2005). They measured Line-Segment Hausdorff Distance for recognition of the shapes of the hand dorsal vein pattern. Badawi was presented a prototyped hand vein verification system and analyzed the statistical performance measures (Badawi 2006). Zhang et al. was proposed a multiscale feature extraction method of hand vein patterns based on ridgelet transform in 2006 (Zang et al. 2006). Shahin et al. was presented a hand vein

authentication system using fast spatial correlation of hand vein patterns in 2007 (Shahin et al. 2007). Wang et al. was evaluated a novel non-invasive imaging technique to image the vein patterns in various parts of the hand for biometric purposes (Wang et al. 2007). In 2008, Bouzida et al. was presented a lock-in infrared thermographic imaging technique for the visualizationof the hand vascular tree (Bouzida et al 2008). In 2009, Khan et al. was used a fast modified PCA algorithm for extracting the features of the hand dorsal vein pattern (Khan 2009). Kumar et al. was presented a new approach for biometric authentication using infrared thermal hand vein patterns and for extraction using knuckle shape information of the hand vein images (Kumar et al. 2009).

Materials and Methods

The proposed hand dorsal vein pattern identification system consists of four stages. These are hand image acquisition, preprocessing of the hand images, feature extraction and recognition. After exploring the literature, it has been observed that there is no common hand dorsal vein database for the researches in this field. Thus, the data used for this recognition system was obtained by NIR illuminated camera. The subcutaneous veins are lying underneath the skin and invisible for naked eyes and also daylight illuminated cameras, so the vascular patterns can’t be determined by using ordinary camera. The blood includes hemoglobin material and this material has higher absorbance between 600-1000 nm wavelength values so the vein tree is seen darker (Wang et al. 2007). In our experiment, the hand images were captured from the back side of the hand by using NIR (near infra-red) illuminated with the wavelength at 880 nm monochromes CCD (charge-coupled device) camera. The image acquisition mechanism includes IR sensitive camera, ring shaped infra-red light source led device mounted to the lens for illumination, the lower platform with two rods (these white head rods are used for refer-ence points for extracting the ROI), the power source and the cable for connection between camera and computer. While acquiring the hand image, the subject leans his\her clenched fists hand against the rods mounted on the lower platform. The image acquisition platform used in this work is shown in Figure 1.

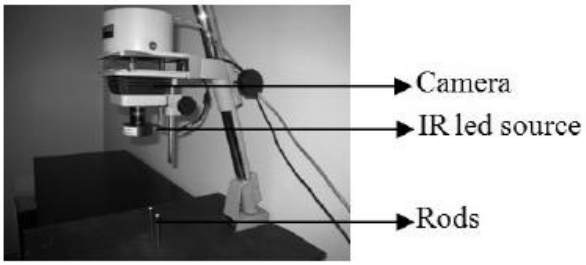


Figure 1. Image acquisition by using NIR camera

A database used in this work includes 927 hand im-ages captured from 103 subjects (9 images per person) of different ages and gender at room temperature (~23 °C) during a month. The images were recorded 752x480 pixels with a gray scaled resolution.

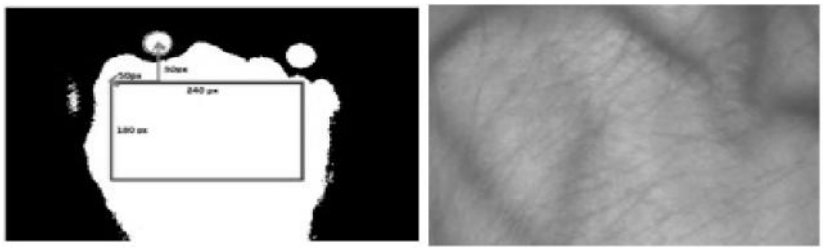
Preprocessing phase includes processes of determining the ROI, eliminating the noises and converting the gray scaled image to the binary formatted image. While determining the ROI, the original image was local thresholded initially as shown in Figure 2. The threshold value is set to 170. Then 7x7 pixels dimensioned circular mask was circulated on the thresholded image. In this method, when the mask found a circular shape then the dimensions of mask were growing up to boundary lines of the circle. This process founds two reference points and signs as the center point of the first one.



(a) (b)

Figure 2. Original image (a), thresholded image (b)

After determining the reference point, the upper left point of ROI is determined by going down 50 pixels from the reference point and 50 pixels left from new point. Then the 240x180 pixels dimensioned rectangle was cropped from gray scaled original hand image as shown in Figure 3.

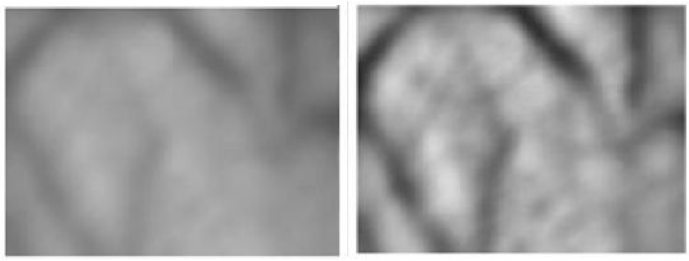


(a) (b)

Figure 3. Cropping process (a), cropped vein image (b)

The next step of the preprocessing phase is removing the noises such as speckles, hairs etc. from the cropped image. For this purpose, 3x3 mean filter and histogram equalization techniques were applied. Mean filtering is an intuitive and easy to implement method of smoothing images. The idea of mean filtering is simply to replace each pixel value in an image with the mean (`average') value of its neighbors, including itself (Boyle and Thomas 1988). We used 3x3 square kernel for filtering the image.

The filtered gray scaled vein pattern image was then histogram equalized. This method adjusts the contrast of the image using the histogram values. A histogram is a graphical representation showing a distribution of pixel values in an image. The intensity values can be better distributed on the histogram through this adjustment. So, the characteristic features of the vein pattern can be more distinctive. The process of equalizing the histogram of an image consists of 4 steps (Umbaugh, 1999): (1) Find the sum of the histogram values. (2) Normalize these values dividing by the total number of pixels. (3) Multiply these normalized values by the maximum gray-level value. (4) Map the new gray level values. The mean filtered and histogram equalized vein pattern image is shown in Figure 4.



(a) (b)

Figure 4. Mean filtered (a), histogram equalized image (b)

The resulting gray scaled image then was converted to Black & White image by using Otsu's thresholding method. Otsu method is generally used for performing the histogram shape-based image thresholding (Otsu 1979). In this algorithm, the image contains foreground and background classes of pixels. Then the optimum thresholding value is calculated for separating those into two classes. The weight, the mean and the variance values are determined for different threshold values. The first step of the algorithm is computing the histogram and probabilities of each intensity level. Then the initial probability weights and mean values are set up. By updating these values and computing intra-class variances, desired threshold value is obtained. Experiments show that when the variance value is close to 0.5, the algorithm gives better result (Umbaugh 1999). The optimum thresholding value is calculated as T=3 in our experiment. The two samples of converted B/W formatted vein pattern image are shown in Figure 5.

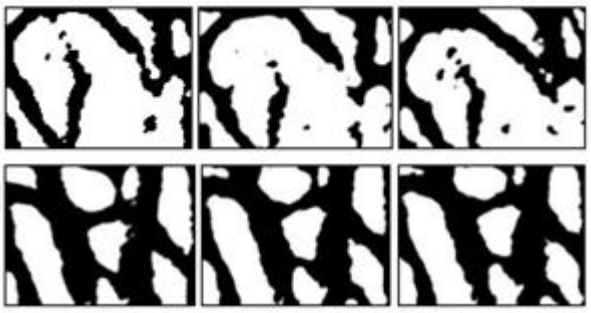


Figure 5. Samples of resulting B/W patterns

A new approach is used for extracting the features of the vein pattern in this experiment. Typically, in hand vein identification researches, thinning and minutiae extraction based methods were used for feature extraction purpose. In our work, the resulting hand vein pattern images were encoded by performing average absolute deviation (AAD) algorithm. This algorithm is defined as (Ma et al. 1996):

$$F = \frac{1}{N}\left(\sum_{i=1}^{N}\left|a(x,y) - m\right|\right) \qquad [1]$$

where N is the number of pixels in the image, m is the mean of that image and a(x,y) is the pixel value at point (x,y). First, 240x180 pixels dimensioned vein pattern images were divided into 20x20 pixels resolution sub-images and then AAD algorithm is implemented to each sub-images. This division process is illustrated as in Figure 6. So, the obtained feature vector has a length of 12*9=108 bytes. The entire feature vectors

were applied to the multi-layered perceptron neural network (MLPNN) as an input for classification of the hand vein patterns.



Figure 6. Division process of vein pattern

In the proposed approach, the recognition of hand dorsal vein pattern images is achieved by using MLPNN. A neural network is a cognitive model trying to simulate biological neurons inside human brain. MLPNN is a feed forward artificial neural network model arranged in three or more layers. These are input layer (includes the information you would to use to make decision), hidden layer(s) (helps network to compute more complicated associations) and output layer (includes the resulting decision).

Each neuron in the input layer is fed directly to the hidden layer neurons via a series of weights. The sum of the products of the weights and the inputs is calculated in each node. The calculated values are fed directly to the output layer neurons via a series of weights. As in hidden layer, the sum of the products of the weights and the hidden layer neuron outputs is calculated in each node in the output layer. If the error between calculated output value and the desired value is more than the error ratio, then the training (changing the weights and calculating the new output by using the new weights) process begins.

This training process can be finished by obtaining the desired error rate for all input combinations (Özbay and Karlık 2002). The structure of basic feed-forward MLP neural network is shown in Figure 7.

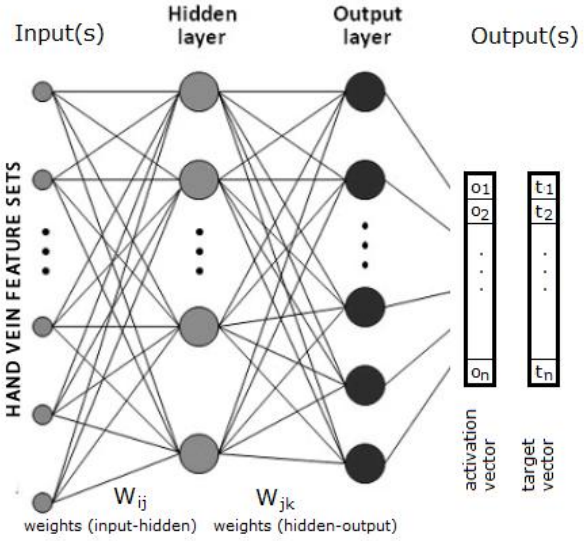


Figure 7. Basic feed forward neural network structure

The neural network algorithm is given below. Let the *net* input to a node in hidden layer be given by

$$net_j = \sum_{i=1}^{n} W_{ji} O_i \qquad [2]$$

and the output of hidden node be

$$O_j = f(net_j) \qquad [3]$$

The activation function (tangent hyperbolic function is used in this work) f is given by

$$O_j = \frac{e^{2(net_j + \theta_j)/\theta_o} - 1}{e^{2(net_j + \theta_j)/\theta_o} + 1} \qquad [4]$$

Now the input to the nodes of output layer is

$$net_k = \sum W_{kj} O_j \qquad [5]$$

and its respective outputs are

$$O_k = f(net_i) \qquad [6]$$

For each input-output pattern, the mean square error can be given by

$$E = \frac{1}{2} \sum_{k} (t_k - O_k)^2 \qquad [7]$$

For any output layer node, ΔW_{kj} will be given by

$$\Delta W_{kj} = \eta(t_k - O_k) f_k(net_k) O_i = \eta \delta_k O_j \quad [8]$$

Similarly for the internal units

$$\Delta W_{ji} = \eta \delta_j O_i \quad [9]$$

To increase the learning rate (η) leading to oscillation is to modify the backpropagation algorithm by including the momentum term α as below:

$$\Delta W_{ji}(n+1) = \eta \delta_j O_i + \alpha \Delta W_{ji}(n) \quad [10]$$

where n is the presentation number and α is constant that determines the effect of previous weight changes on current direction of movement in the weight space.

The back-propagation algorithm is based on the selection of a suitable error function. These error values are determined by the actual and desired outputs of the network. The output is dependent on the network parameters such as the weights and the thresholds (Jacek 1992). This algorithm uses two parameters while working. These are learning rate and momentum. Both of these parameters affect the learning process. Experiments show that the learning rate is best between 0.1-0.3, and the momentum is best between 0.7-0.9 (Shanthi et al. 2009). We used three different back-propagation algorithms. These are online, batch and quick back-propagation algorithms. Online back-propagation algorithm is the most preferable algorithm used in training. It adjusts the weights according to the gradient calculated by the backward transfer mechanism. It adjusts the weights after each input pattern is elaborated; therefore it is called 'online'. Batch back-propagation algorithm is a variant of online algorithm. Because it works like online learning except the adjustments of weights are implemented after all input pattern is elaborated (at the end of each epoch). Quick propagation algorithm differs from other two mentioned here. This algorithm doesn't use adaptive learning rule. Each weight is considered separately (Shanthi et al. 2009).

Results

In order to evaluate the recognition of the vascular pat-tern feature sets, learning based multi-layer perceptron neural network is performed in this experiment. Three different learning algorithms are utilized. These are quick propagation (QP), online back-propagation (OBP) and batch back-propagation (BBP). Tangent hyperbolic transfer function is used for activation of neurons. Mean square error (MSE) function is

exploited for measuring the training performance of the network. The value of MSE is used to determine how well the network output fits the desired output. The stop criteria used in this work is based on MSE.

The network includes one input, one hidden and one output layers. The number of neurons in hidden layer is determined by using heuristic method. The best structure of network is found as: 108 (input feature set) – 101 (neuron number in hidden layer) – 103 (number of subjects). Besides that, the parameters; momentum and learning rate of the network are defined as 0.7 and 0.3 respectively.

The proposed system was tested over a database of vein pattern collected from 103 subjects. This image database consists of 927 gray-scaled hand images (9 images per person). Prior to perform the identification phase, 70% of all images selected randomly are used for training (TRN) the network, 15% of that is for validation (VLD) and the rest (15%) is used for testing (TST). The verification data is used to prevent over fitting of the network. The implementation of classification process is run twice. The testing times are below one second so they did not included in table. The testing results obtained in this experiment are given in Table I. As it can be seen from the table, batch back-propagation algorithm gives the best results for testing process.

Table 1. Experimental Results of Correct Classification Rates (%)

	TRN	VLD	TST	Iteration	Training Time (sec.)
Quick Propagation	100	97.2	98.9	307	162
.	100	98.3	98.9	48	26
Online BackProp.	100	97.8	98.9	204	145
	100	95.1	96.7	152	103
Batch BackProp.	100	98.9	100	3231	1733
	100	98.9	100	1011	808

Discussion

Artificial neural network based hand dorsal vein identification system has been designed and implemented in this work. The hand vascular images were acquired by using near-infrared illuminated camera and pre-processed for getting discriminating features of the vein tree pattern. First, the vein region has been obtained by using the reference point previously determined. Then, the images were enhanced by applying mean filter and histogram equalization and then transformed to B/W format. Average

absolute deviation algorithm is used for getting the vein pattern information. For this purpose, the ROI were divided into sub-images then the feature extraction process was performed to each sub-images.

We proposed a new approach based on multi-layer perceptron neural network method in recognition level of hand dorsal vein identification system. The feature sets were fed into input layer of network and training phase was performed. The performance of the proposed system is satisfactory. The best performance is achieved in batch back-propagation learning algorithm as all testing input feature vectors are classified correctly.

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