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Design a Biometric Identification System Based on the Fusion of Hand Geometry and Backhand Patterns

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ABSTRACT

This paper describes the design and development of a prototype system for the automatic identification of an individual based on the fusion of hand geometry with backhand patterns. Information fusion at the feature extraction and at the confidence level, where the matching scores reported by Bayesian backpropagation neural network, is discussed.

The system was tested with the template files. The test performance, False Acceptance Rate (FAR) = 10% and False Rejection Rate (FRR) = 0%, suggests that the system can be used in medium/high security large buildings environments.

Keywords: *Identification, hand geometry, backhand patterns, Bayesian backpropagation neural network.*

نظام التمييز المعتمد على دمج بصمة جغرافية الكف مع خريطة ظاهر الكف

الملخص

يهدف البحث الى تصميم وتطوير نظام لتمييز الافراد معتمدا على دمج بصمة جغرافية الكـف مع خريطة ظاهر الكف، الاندماج الناتج زاد من كفاءة النظام ومن قابليته الامنية. تطلب العمل معالجة للصورة لغرض استخراج البيانات اللازمة.

تم في هذا البحث ايضا استخدام شبكة Bayesian bakbpropation العـصبية فـي عمليـة استخلاص ختم رقمي خاص بكل صورة كف.

تم اختبار وفحص النظام لعينات متشابهة ومختلفة وكانت النتيجة (نسبة خطأ القبـول=10%- نسبة خط الرفض=0%). ان هذا النظام مهيأ للاستخدام في امن الـشركات والبنايـات مـن المتطفلين.

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1. INTRODUCTION

Traditional user-identification techniques based on passwords, personal identification numbers (PINs), card keys, etc., cannot differentiate between an authorized person and a fraudulent impostor [1]. Biometrics is an emerging technology [2] that identifies users by their physical and/or behavioral characteristics, and inherently requires that the user to be identified is physically present at the point of identification.

A biometric system may operate either in *verification* mode or *identification* mode:

- In the verification mode, the system validates a person’s identity by comparing the captured biometric data with her own biometric template(s) stored system database. In such a system, an individual who desires to be recognized claims an identity and the system conducts a one-tone comparison to determine whether the claim is true or not. Identity verification is typically used for *positive recognition*, where the aim is to prevent multiple people from using the same identity [3].
- In the identification mode, the system recognizes an individual by searching the templates of all the users in the database for a match. Therefore, the system conducts a one-to-many comparison to establish an individual’s identity (or fails if the subject is not enrolled in the system database) without the subject having to claim an identity. Identification is a critical component in *negative recognition* applications where the system establishes whether the person is who she (implicitly or explicitly) denies to be. The purpose of negative recognition is to prevent a single person from using multiple identities [3]. Identification may also be used in positive recognition for convenience (the user is not required to claim an identity).

The block diagrams of a verification system and an identification system are depicted in Fig. 1.

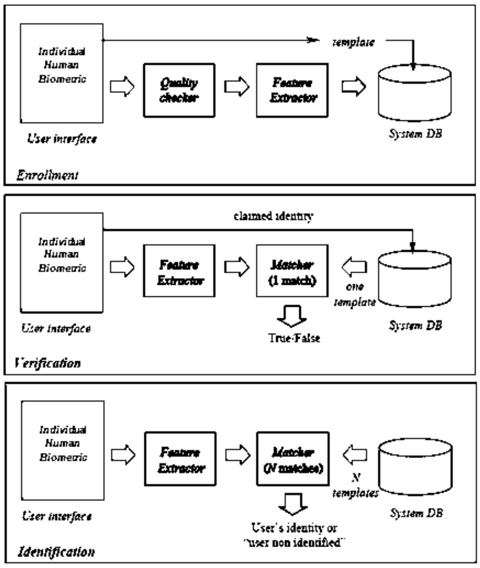


Figure 1: Block diagrams of enrollment, verification and identification tasks

The physical characteristics of an individual that are most often used in identification/verification systems based on biometrics are as follows: fingerprint, hand geometry, face, palmprint, iris, retina, signature and voice [4]. However, a single physical characteristic of an individual sometimes fails to be sufficient for an identification, for this reason multimodal biometric systems, which integrate two or more different biometric characteristics (e.g., a face, a fingerprint and hand geometry [5], or a face, voice and a lip movement [1]), are being developed to provide a more secure identification/verification system to identify individuals.

There has been several hand geometry verification systems published in literature. Jain et al. [6] developed a pegged hand geometry verification system for web security. Later Jain and Duta [7] developed another pegged system which aligns the two images and define a metric, Mean Alignment Error as the average distance between corresponding points measured between the images to be verified. Wong and Shi [8] developed system which uses a hierarchical recognition process, with gaussian mixture model used for the one set of features and a distance metric classification for a different set of features.

This paper describes the prototype of a biometric identification system based on a fusion of hand geometry with backhand patterns. As mentioned, there are some bibliographic references relating to hand biometrics, as well as references about commercial systems that are available. So as far as we know, there are no references about systems based on the fusion of hand geometry with backhand patterns. The proposed system uses two levels: backhand feature extraction level and Bayesian backpropagation neural network for the fusion stamp level.

2. FEATURE EXTRACTION

2.1 Image acquisition

An important and difficult step of an hand recognition system is image acquisition. We have designed our own device for iris image acquisition, which can deliver backhand image of sufficiently high quality. In which the process of measurement is being fast, comfortable as well as robust against natural systems.

The first part of the device is the fund which to be in the form of a dark color so as not to enter any external lighting blurring the image. This fund should be plastic tarpaulins black-high (45 cm) dimension, sufficient to enable the camera installed within the fund to take full picture desist hand. This is as shown in Fig. 2:

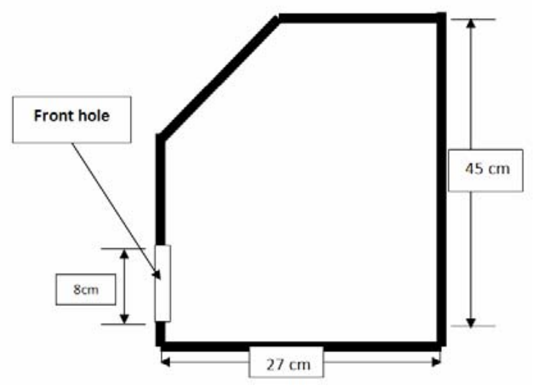


Figure 2: The hand entrance fund

The length of the bar of its base is (27 cm) height manner so that whatever the hand of any size to prove the rule and be within the scope of the picture. This is as shown in Fig. 3:

Figure 3: the base of hand geometry

At the bottom of the interface device there is along the slot bar a base with the height (8 cm).This is to enable the user to enter his hand freely and to install the appropriate status of the base so that the device can identify the person or add information to outweigh where not added. The process of being refined to the fund from the inside paper refinement is found in order to have black dark-reflector for lighting. Lighting is only brought to the fund, not by a simple lighting, and this process is called (Abundance of Plastic).

The camera is inside the fund body, a creative with accuracy (600 * 800) which is precision enough to distinguish geographical desist. This demonstrates the level of vertical camera on a device to be suitable for a base up to (45 cm) to take full picture to desist. This camera (which is a web cam type Vista) linked with the computer through the (USB) hole. The way to pick up the image is done by computer program (MATLAB) and the picture is processed this program also, this will be dealt with later in this project.

There are four pickets installed on the base in the certain they are used to install places, hand on the base and to prevent it from moving. The diameter of each pickets not to exceed (10 mm) width and (1.5 cm) height. Pegs and manufactured plastic transparent following illustrative picture of the pickets are supplied with the way to install a stop. This is shown in Fig. 4:

Figure 4: Sample of backhand acquisition image

It is important to know that the lighting to be fixed any (Standard) at all the times and places. The form (neon) working on (220 volts) and lighting are brought on to the machine.

2.2 Preprocessing and feature extraction

When the person's hand image acquireed, the program in MATLAB takes the picture soon and analyzes it to the three main colors (R,G, B) as shown in Fig. 5.

Then the hand extraction process is achieved by taking the hand image and apply black background masking in order to remove its effect.

Each one of the three resulting images will be divided into 100 segments, then a standard deviation (STD) can be taken for each square segment. The equation (1) refers to (STD) equation.

$$STD_j = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}(A_i - M_i)^2} \quad j=1,2,\ldots,100 \;\ldots\ldots\; (1)$$

Where N represents the number of pixels in each section
A_i represents the intensity of i-th pixel in the section,
M_i represents the mean value of window's pixels

After taking the STDs for each image we obtain three matrices of one hundred elements later these matrices are merged to obtain one matrix of (300) elements. These will represent the database for each person.

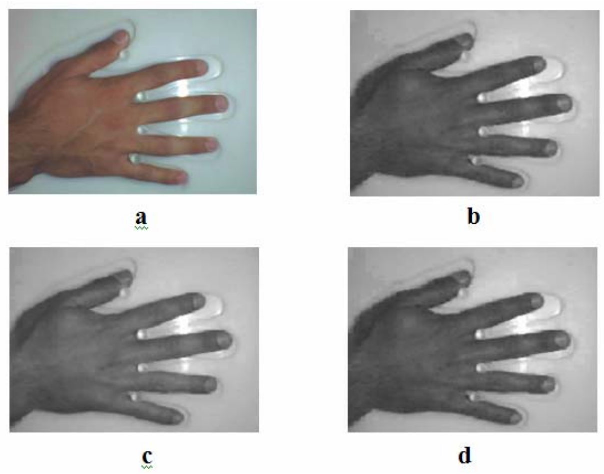


Figure 5: a - Original RGB imag
b - Red level image
c - Green level image
d - Blue level image

3. NEURAL NETWORKS

<u>3.1 Facility of Neural networks</u>

The neural network techniques could be adopted for the purpose of comparison and recognition.

Applications using such nets can be found virtually in every field that uses neural nets for problems that involve mapping a given set of inputs to a specified set of target outputs [9]. As is the case with most neural networks, the aim is to train the net to achieve a balance between the ability to respond correctly to the input patterns that are used for training (memorization) and the ability to give reasonable (good) responses to input that is similar, but not identical, to that used in training (generalization).

3.2 Bayesian Backpropagation neural network

Properly trained Bayesian backpropaga-tion networks tend to give reasonable answers when presented with inputs that they have never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input/target pairs and get good results without training the network on all possible input/output pairs[10].

Although a single-layer net is severely limited in the mappings it can learn, a multilayer net (with one or more hidden layers) can learn many continuous mapping to an arbitrary accuracy. More than one hidden layer may be beneficial for some applications, but one hidden layer is sufficient [9].

Bayesian backpropagation is a network training that updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well. The process is called Bayesian regularization [10].

This Bayesian regularization takes place within the Levenberg-Marquardt algorithm. Backpropagation is used to calculate the Jacobian *jX* of performance with respect to the weight and bias variables *X*. Each variable is adjusted according to Levenberg-Marquardt, as shown in equations (2,3,4).

$$jj = jX * jX \quad \text{.……………………………...} \quad (2)$$

$$je = jX * E \quad \text{……………………………...} \quad (3)$$

$$dX = -(jj+I*mu) \setminus je \quad \text{..…………………...} \quad (4)$$

Where *E* is all errors and *I* is the identity matrix. The adaptive value *mu* is increased by *mu_inc* until the change shown above results in a reduced performance value. The change is then made to the network and *mu* is decreased by *mu_dec*. The parameter *mem_reduc* indicates how to use memory and speed to calculate the Jacobian *jX*. If *mem_reduc* is 1, then train Levenberg-Marquardt runs the fastest, but can require a lot of memory. Increasing *mem_reduc* to 2 cuts some of the memory required by a factor of two, but slows train Levenberg-Marquardt somewhat. Higher values continue to decrease the amount of memory needed and increase the training times [10].

3.3 Suggested topology

The Bayesian backpropagation network which is suggested has one node in the input layer, forty nodes in the hidden layer and one node in the output layer. The activation functions used are tan-sigmoid activation functions in the hidden layer and pure-linear activation function in the output layer. And Levenberg-Marquardt optimization is used to regulate convergence. By this topology the Bayesian backpropagation network is able to recognize a sample among different backhand images.

As mentioned previously, image segmented into 300 square matrixes and the standard deviation (STD) calculated for each segment as (STD1, STD2, ………, STD300). These values flow serially to the input layer for training.

Moreover, the performance of Bayesian backpropagation network can be found by the performance error in equation (5).

$E = mse(\sum t_i - y_i) \quad i=1,2,\ldots,300$ …..…….. (5)

Where *mse* is the mean squared error, *t* is the stamp target and *y* is the neural network output.

4. RESULTS

It is important to see differences between the backhand images for different persons and a convergence between the backhand images for the same person in data values. After image segmentation, taking STD values for each image segment may give suitable results because of its features, where it reduces the huge numbers of backhand image data and exhibits the variations between image segments. This step prepares the backhand pattern data to be used in the next stage neural network. Fig. 6 shows that the STD values for two images had the same backhand pattern. It proves that image data is nearly for the same backhand person pattern.

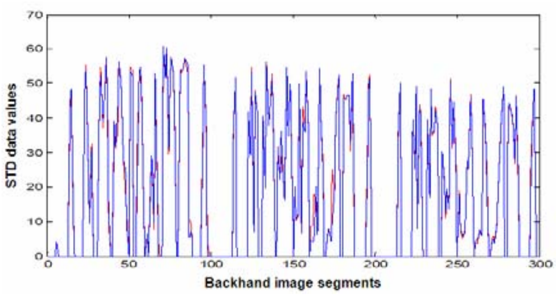


Figure 6: STD curves of two backhand segmentation images for the same person

In the previous figure, the little differences for the values between the two images are due to the random noise from camera. This equilization for the same iris images STD values will lead to give different STD curves between different backhand images. Fig. 7 below shows the differences between the different backhand images for two persons:

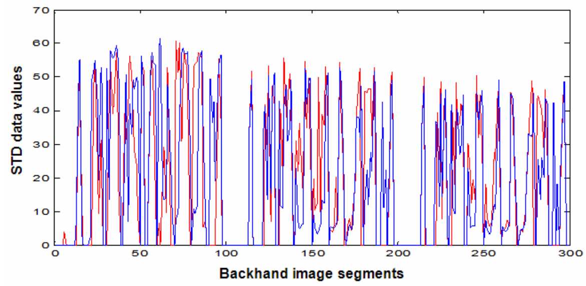


Fig. 7: STD curves of the different backhand images for two persons

The Bayesian backpropagation network topology, as shown in Fig. 4, is a multiple-layer consisting of 1 node for input, 40 nodes for hidden and 1 node for output. It has 121 weights and biases to be stored in a database file. The data input stream is serial for each backhand image.

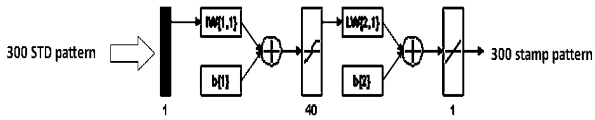
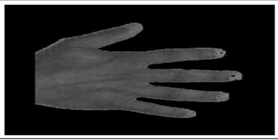


Figure 4: Bayesian backpropagation network architecture

Such that any hand introduced to the system can be identified if it is on these trained sample and reject if it is out the trained samples. The calculated weights (including biases) are stored in a database file and become the comparison base to detect any other backhand image. Every backhand image to be tested enters the network in the same way, the output values will be compared with the outputs of the original image.

Table I illustrates some stamp samples that are used as backhand image targets.

Table I: Samples of binary stamps and person's backhand

Person index	Binary stamp sample	Backhand sample
Person 1		
Person 2		
Person 3		

In identifying the person the new image will not be stored in text file; else it will be compared with the database of all persons and the image of less error or less difference form the new image that will represent the person. Tolerance of (0.004) is used. If the person does not exist the less different will be larger than this tolerance so he will not be identified. The system was tested with the template file; the test performance attained FAR 10% and FRR 0%.

The FAR and FRR can be calculated according to the following equations:

$$\mathrm{FAR} = \frac{\text{Number of accepted imposter claims}}{\text{Total number of imposter accesses}} \times 100\% \quad ....(6)$$

$$\mathrm{FRR} = \frac{\text{Number of rejected genuine claims}}{\text{Total number of genuine accesses}} \times 100\% \quad ....(7)$$

5. CONCLUSION

In this paper, a powerful practical identification system is designed based on the fusion of hand geometry and backhand patterns. This system has the ability to discriminate 100 samples with capability to extend this discriminations power to any required number according to the application.

The equivalent tolerance found by experiments, was attained to (0.004). Moreover, in this research False Acceptance Rate (FAR) reached to 10% and False Rejection Rate (FRR) to 0%.

To acquire all the data necessary for the target from 3 image colors image processing techniques were adopted. Then (300) STD statistical values were employed to accommodate the acquired image data with the input of the neural network.

Bayesian backpropagation trained neural network was used for the fusion stamp extraction, with the following topology:

1- The network contains one node on input layer, forty nodes on hidden layer and one node on output layer.
2- The activation functions used are: sigmoid activation function for the hidden layer and pure-linear activation function for the output layer.
3- And Levenberg-Marquardt optimization is used to regulate convergence.

The system is regarded as highly accurate as well as easy in use in biometric authentication systems.

Further work should be undertaken to increase the database size with template files collected over a longer period of time, as well as experimenting with novel backhand characteristics like datum points and global texture features.

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