Human Authentication with Earprint for Secure Telephone System

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Abstract: This paper describes the design and development of a prototype system for the automatic authentication of an individual based on the human ear patterns. Information at the feature extraction and at the confidence level, where the matching scores are reported by Probabilistic neural network, is discussed.

The system was tested with the template files. The test performance reaching False Rejection Rate (FRR) = 9% and False Acceptance Rate (FAR) = 9%, suggests that the system can be used in telephone security environments.

Keywords: *Authentication, Earprint, Image preprocessing, Probabilistic neural network.*

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1. INTRODUCTION

Biometrics is the study of automated methods for recognizing a person based on his physical or behavioral characteristics [1].

The idea of biometric identification is very old. The methods of imprints, handwritten signatures are still in use. The photographs on the identification cards are still an important way for verifying the identity of a person. But developing technology is paving the way for automated biometric identification and is now a highly interesting area of research [1].

Since the characteristics for each human are distinct and unique, biometrics provides a more reliable system than the other traditional systems, such as identity cards, keys, and passwords [2].

Researchers have done different biometric authentication works; as in 2003, T.C. et. al. worked on Secure Smartcard-Based fingerprint [3]. In 2005, Abou E., hides irisprint for authentication of digital images [4]. In 2009, Fadwa and Raid used invariant moment features for faceprint [5]. And in 2011: Naidu et. al. dealt with palmprint authentication system with wavelet [6], also K.S. et. al. used retinalprint authentication with key exchange system [7]. Ear biometrics, on the other hand, has received scant attention [2]. See Fig. 1 [1].

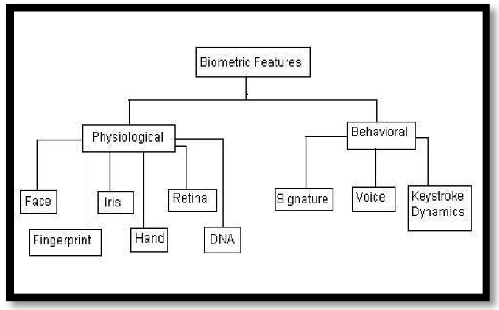

Fig.1 Different types of biometric features

The ear was first used in 1989 to authenticate people being by Iannarelli [8] where manual techniques to identify ear images were used. In 1999, Moreno et al. with outer ear images for personal identification [9] used Borda, Bayesian and Weighted Bayesian combination with 2D intensity images of ears for identification. In 2002, Victor et al. evaluated between Ear and Face Biometrics [10] and in 2003, Chang et al. made a combination of face and ear images with appearance-based biometrics [11] also made comparisons between ear and face biometrics and the Eigen ear image was used for ear recognition. And in 2007, M. Ali and et. al. also worked on ear [12] by applying new ear identification approach using wavelets for human recognition.

This paper describes the prototype of a biometric authentication system based on earprint for telephone security environments. The proposed system uses two main levels: image preprocessing of ear pictures and Probabilistic neural network.

2. FEATURE EXTRACTION

2.1 Acquisition of ear image

The first and most important step of earprint authentication system is image acquisition. Our own device is designed to deliver the ear image of sufficiently high quality.

The device consists of the cabin to prevent any external light from distorting the image. This cabin can be material of plastic or alumina with latitude high enough to enable different human sizes.

The camera is installed inside the box to take a full picture of the ear. This box is movable on a slice to cover tall or short people. This is as shown in Fig. 2.

Figure 2: The Cabin with slicing box

The camera is inside the slicing box with accuracy (480 * 640) which is precise enough to distinguish geographical desist. This demonstrates the level of farness of the camera on a device to be suitable for a base to take full picture to desist. This camera (which is a web cam) is linked with the computer through the Universal Serial Bus (USB) port. The way to pick up the image was from the MATLAB program then the picture can be processed by this program too.

It is important to know that the lighting can be fixed in any standard at all times. The form lights of diodes working with the web cam inside the slice box solve the problem.

2.2 Pre-processing of ear image

When the human ear image is acquired, the program in MATLAB takes the picture promptly and crops it to get the earprint, as shown in Fig. 3.

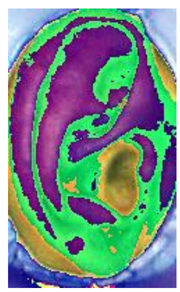

Figure 3: Sample of earprint image

Then, the resizing process into (240×320) pixel is done to equalize the sizing of different cropped ear images. After that, the resized image is divided into its basic three image colors Red (R), Green (G) and Blue (B). See Fig. 4.

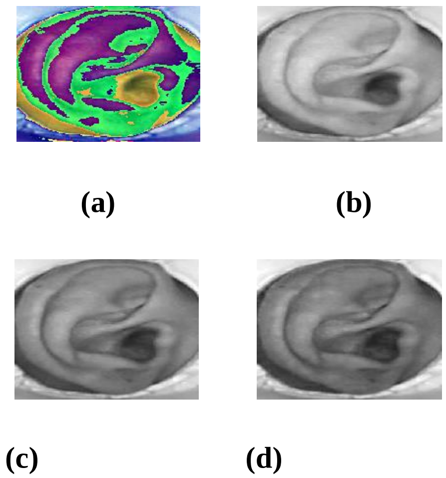

Figure 4: (a) Original RGB image
(b) Red level image
(c) Green level image
(d) Blue level image

Then the earprint extraction process is achieved at this stage by dividing the ear image (for each color part) into 30 square boxes (each of 24×32 pixels) and the average is calculated for each square box. Then the Mean Absolute Deviation (MAD) is computed for each 10 average box values, because it is suitable for this application (that is each box has 24×32 pixels when the whole image has 240×320 pixels).

When using the MAD, the Block Matching block estimates the displacement of the center pixel of the block as the *(d_1, d2)* values that minimize the following MAD equation [13]:

$$MAD(d_1,d_2) = \frac{1}{N_1 \times N_2} \sum \sum_{(n_1,n_2),\in B} | s(n_1,n_2,k) - s(n_1+d_1,n_2+d_2,k+1) |$$

…………………………………….(1)

Where:

(d_1,d_2) is the displacement of the center pixel of the block

$N_1 \times N_2$ are the size of the Block of pixels.

(n_1,n_2) is the pixel location

k is the image color part

B is the Block of pixels.

After taking the MADs values for the image three matrices of ten elements to each one are obtained, thus these three matrices are merged to obtain one matrix of (30) elements. These will represent the database for each human earprint.

3. NEURAL NETWORKS

3.1 Neural networks Facility

Applications using neural networks can be found virtually in every field that uses the neural networks for problems that involve mapping a given set of inputs to a specified set of target outputs [14]. 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 the input that is similar, but not identical, to that used in training (generalization) [15].

3.2 Probabilistic neural network

Probabilistic neural networks can be used for classification problems. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, compete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes. The architecture for this system is shown in Fig. 5 [16].

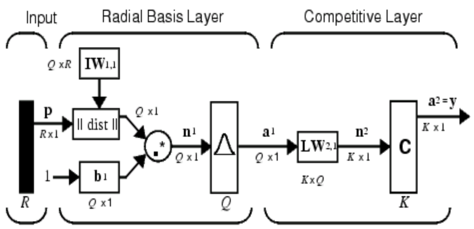

Fig. 5 Probabilistic network architecture

From this figure, it is assumed that there are Q input vector/target vector pairs. Each target vector has K elements. One of these elements is 1 and the rest are 0. Thus, each input vector R is associated with one of K classes [16]. Thus, the probabilistic neural network basically consists of two layers.

First layer (hidden layer) is the radial basis function which train by the following equation [16] [17]:

$$a l_i = radbas(\| I W_{1,1\,i} - p \| b l_i) \quad \text{....(2)}$$

Where:

i is the i^{th} element

al is the output of the hidden layer

$IW_{1,1}$ is the weight matrix of the hidden layer

p is the input matrix

bl is the bias matrix of the hidden layer

Second layer (output layer) is the competition function which is trained by equation (3) [16]:

$$a^2 = compet(LW^{2,1}a^1) \quad \text{............(3)}$$

Where:

a^2 is the output of the output layer

a^1 is the output of the hidden layer

$LW_{1,1}$ is the weight matrix of the output layer

The most extreme form of competition among a group of neurons is called Winner Takes All. That is; only one neuron in the competition functions will have a nonzero output signal when the competition is completed [14]. It uses the dot product of the input vector (here the output of the hidden) and the weight vector method for determining the closest weight vector to a pattern vector, where the dot product method is based on the assumption that the weight vector for each cluster (output) unit serves as an exemplar for the input vectors that have been assigned to that unit [14] [18].

In this research, the number of nodes in the input layer is always equal to 30 neurons, but for hidden and output nodes it is according to the number of persons who can use the phone line.

4. AUTHENTICATED EARPRINT

The input nodes of the probabilistic neural network represent the extracted MAD values from each earprint image where each output node represents a person. So, the target values describe the authenticated values; that is, a true node or person equals 1 and all other values for false nodes or persons equal 0.

See Fig. 6 which represents the program panel of the earprint system, where this figure illustrates how the user can add, search, remove and control the phone line. Fig. 7 and Fig. 8 both show an indicating message box to illustrate that the human can use the phone line or not after the authorizing process.

If the same earprint authenticated to the same person then the Matlab program can send 5v to any limited output pin in the parallel port then a relay will be on in order to make the phone line work. By the same words, if the earprint authenticated to the wrong person then the Matlab program can send 0v to the limited output pin in parallel port then a relay will be off in order to make the phone line not to work. See Fig. 9 for the flowchart of the suggested system. This figure describes the preprocessing of an earprint image until extracting the database and then stores this data or compares it with the template file. Then the authorized will appear to decide if the phone line is to be on or still off.

Fig. 6: Program panel of earprint system

Fig. 7: Message box indicate true to use phone line

Fig. 8: Message box indicate false to use phone line

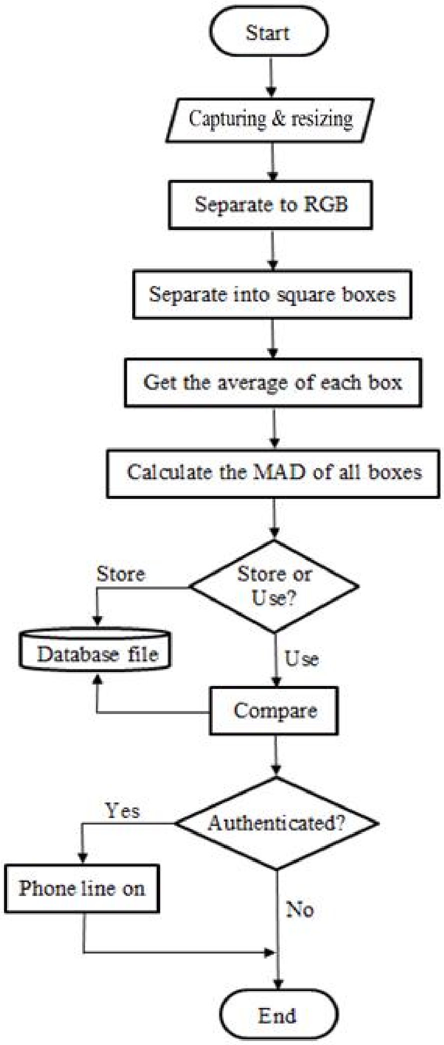

Fig. 9: Suggested system flowchart

5. RESULTS

It is important to see a convergence between the ear images for the same human in data values and the differences between the ear images for different humans. After the earprint extraction process, taking MAD values for each image may give suitable results because of its features, where it reduces the huge numbers of ear image data and exhibits the variations between images. This step prepares the earprint data to be used in the next stage neural network. Fig. 10 shows the differences between the different MAD values of five earprints for different humans.

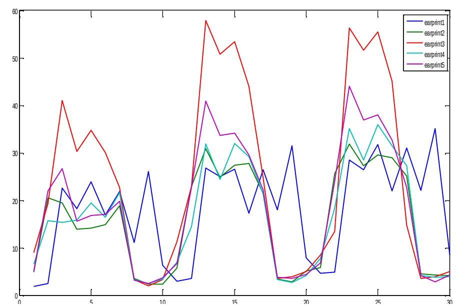

Fig. 10: MAD values of the different earprints for five humans

Figure 11 shows the MAD values of five earprints for the same human. It proves that earprint data is very near for the same human.

In the last two figures, it is clear that there are very little differences for the MAD values between the five earprints of the same human. This equalization for the same MAD values will lead to giving clear different MAD curves between different human earprints in Fig. 10.

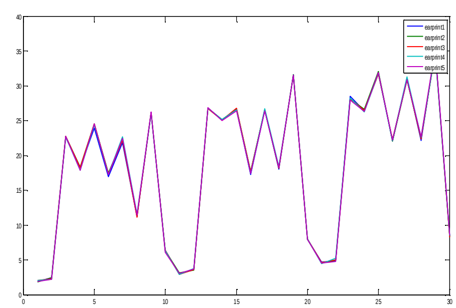

Fig.11: MAD values of five earprints for the same human

The suggested Probabilistic neural network, as shown in Fig. 12, is a multiple-layer consisting of two layers; the first layer uses radial basis function and the second layer uses competition function.

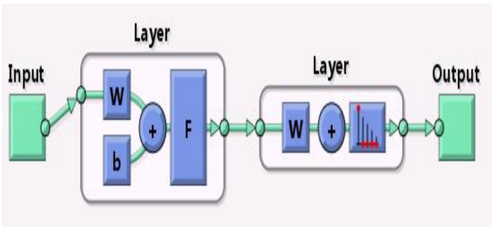

Fig. 12 Probabilistic neural network in a Matlab program

In Probabilistic neural network the number of presented earprints reached 200 earprints; one hundred earprints is for the training stage and the other one hundred earprints is for the testing stage.

So as that any earprint introduced to the system can be authenticated if it is on these trained samples and rejected if it is out of the trained samples, the calculated weights (including biases) are stored and become the comparison base to detect any other earprints.

For the output values the FRR and FAR can be calculated to verify the results according to the following equations [19] [20]:

$$FRR = \frac{Number\ of\ rejected\ genuine\ claims}{Total\ number\ of\ genuine\ accesses} \times 100\% \quad ..(4)$$

$$FAR = \frac{Numberof\ acceptedimposterclaims}{Totalnumberof\ imposteraccesses} \times 100\% \quad ..(5)$$

In this research the False Rejection Rate (FRR) reaches 9% and False Acceptance Rate (FAR) reaches 9%, these performances are due to the wrong ear entrance by humans.

It is worth mentioning that the skin color and hair density also affect the earprint in the authentication process. Thus here is the designed cabin for keeping the earprint with less environment noise.

6. CONCLUSION

In this paper, a practical authentication system is designed based on the earprint of humans for switching a telephone line. There were two main steps to reach the goal. First: applying image pre-processing techniques on the ear image for data acquisition. Second: applying probabilistic neural network for authentication.

The image pre-processing techniques display the steps for getting the earprint necessary for extracting data starting from the acquisition of the image, image cropping, image resizing, image extraction to the three main color parts and image dividing into small square boxes. Then the average of every square box is computed. After that MAD values are calculated to be used in the neural network for recognition.

For neural network techniques, Probabilistic neural network was used for authentication. The weights and bias will be stored to be used later in the recognition. The number of image samples used in this research is equal to 200 ear images, where the input nodes of the neural network represent the MAD values for each earprint and every output node of the neural network represents a human to be authenticated.

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