Analysis Of Thumbprint Recognition In Different Bit Levels

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***Abstract*— In this paper, a preliminary analysis of thumbprint recognition in different bit levels is presented. A digital image consists of *m x n* pixels and each pixel is represented by gray level value. In an 8-bits gray level image, the gray level value range from 0 to 255 for each pixel. Each bit-plane will then be extracted as the input into the neural network to test its performance and accuracy. The performance is then evaluated based on the recognition rate of each bit plane.**

Keywords- Thumbprint recognition; bit level extraction; image processing; neural network.

I. INTRODUCTION

Biometric technology provides the best solution in security system where human characteristics which is unique for each human is applied. This technology has been used to measure and identify an individual's identity through physiological or behavioral trait [1]. Fingerprint biometric has been the most popular and widely applied among all biometric technologies and has been applied in various applications especially in forensic and access control [2].

The classification of fingerprints was firstly proposed by Galton [3] with three major fingerprint classes that are the arch, whorl and loop. Later, Henry [4] modified Galton's classification and came out with eight classes which consist of Right Loop, Left Loop, Whorl, Plain Arch, Central Pocket, Tented Arch, Accident and Twin Loop. The four major classes of the fingerprint classification are shown in Figure 1.

Arch Whorl Right Loop Left Loop

Figure 1. Examples of four major fingerprint classes

There are two major features in a fingerprint/thumbprint that are mostly extracted out for classification: 1) the global ridge and furrow structures located at the central region of the fingerprint which formed special patterns. 2) Local ridge and furrow minute details. Basically, information extraction from ridge structures can be performed by developing a mathematical model of the fingerprint ridge. Also, another method is by recoding the characteristics of the ridges and the information is stored for classification [5].

In fingerprint / thumbprint identification, mostly minutiae-based and correlation-based approaches are implied. For minutiae-based approach, it detects the minutia position, minutia direction, and the type of minutia which is either the ending or bifurcation in a fingerprint / thumbprint image [6][7]. As for correlation-based, it is a process of matching two fingerprint / thumbprint images directly.

Furthermore, gray level and binarized images are usually applied for feature extraction algorithms. Commonly, gray level images are applied with ridge following [8]. As for binarized images, they are used in approaches that involve minutiae detection after the process of thinning the binary image [2]. Some approaches that involve binarization are optimal thresholding, adaptive, and peak detection [9].

Previous research has shown a convincing result in applying bit-plane extraction into face recognition [10]. Hence, in this project, gray level images are used and the thumbprint feature is extracted into different bit levels. Database used here is from FVC2000 [11]. After different bit levels are extracted out from the original image, they are then fed into neural network for classification. Analysis for the thumbprint recognition at different bit level is then performed.

II. THEORETICAL BACKGROUND

A digital image is constructed by multilevel information of bits. It consists of *m x n* pixels and each pixel is represented by gray level value.

As stated by Gonzalez [12], higher order bits consists of most of the information in an image, while lower order bits contains only subtle details. Hence, in an 8-bit image, it will form 8 bit-planes ranging from bit-plane 7 as the highest order bit and bit-plane 0 as the lowest order bit.

Bit level can be extracted mathematically from gray-level image. The gray-level can be derived as in Equation (1).

$$f(x,y) = \begin{bmatrix} f(0,0) & f(0,1) & \dots & f(0,N-1) \\ f(1,0) & f(1,1) & \dots & f(1,N-1) \\ \vdots & \vdots & \dots & \vdots \\ f(M-1,0) & f(M-1,1) & \dots & f(M-1,N-1) \end{bmatrix} \quad (1)$$

978-0-7695-4959-0/13 $25.00 © 2013 IEEE
DOI 10.1109/ACSAT.2012.53

The process of the bit level extraction can be summarized in Equation (2).

$$f_{bp_i}(x, y) = R\left[\frac{1}{2}\, floor\left(\frac{1}{2^i}\left[f(x, y)\right]\right)\right]$$

i=0, 1, 2…7 *(2)*

where *f(x,y)* is original image,
fbp(x,y) is bit-plane information,
R is the remainder, and
floor(x) is round the elements to x nearest integers less than or equal to x.

The database applied is the FVC2000 from Biometric System Laboratory University of Bologna [11]. There are four different databases provided where each database is collected using different sensors or technologies. The sensors used include a low-cost optical sensor, low-cost capacitive sensor, optical sensor and synthetic generator. There are 880 fingerprints in each database with 110 fingers wide and 8 impressions per finger deep. In this project, a database of 16 set of images are applied. Each set of the thumbprint consists of 8 different thumbprint images. The images of the database are shown in Figure (2).

Figure 2. Example of subjects from FVC2000 thumbprint database [11].

Figure (3) shows the output of different bit levels extracted out from an original image. As mention previously, it shows that lower order bit level displayed less significant images while higher order bit level shows a more vivid image of the original image.

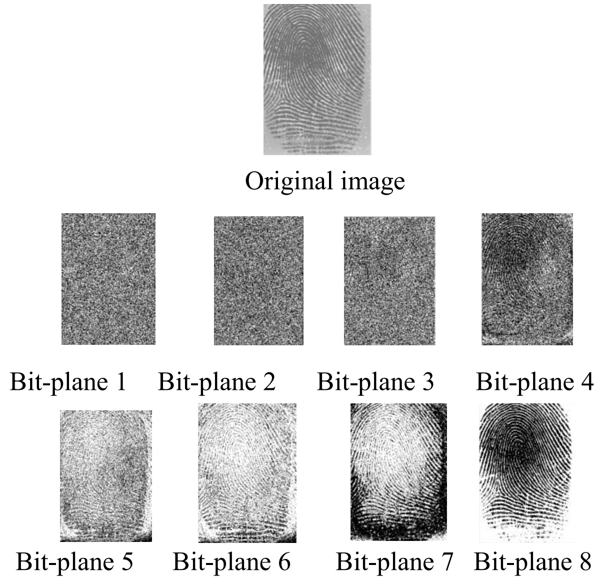

Figure 3. Example of bit plane extraction for thumbprint.

Neural network is used for classification in this project. The type of neural network applied is the Multilayer Perceptron Neural Network.

Basically, perceptron is applied in feed forward network. The input of the neuron is the weighted sum of the inputs plus the bias term. The output of the network is formed by the activation of the output neuron, which is sum function of the input:

$$y = F\left(\sum_{i=0}^{n} w_i x_i + \theta\right) \quad (3)$$

The activation function F can be linear so that it can be linear network or nonlinear. This section, it will be considered as the threshold function:

$$F(x) = \begin{cases} 1 & \text{if } s > 0 \\ -1 & \text{otherwise} \end{cases} \quad (4)$$

The output of the network thus is either +1 or -1, depending on the input. The network can now be used for a classification task: it can decide whether an input pattern belongs to one of two classes. If the total input is positive, the pattern will be assigned to class +1, if the total input is negative, the sample will be assigned to class -1. The separation between the two classes in this case is a straight line, it given by the equation:

$$w_1 x_1 + w_2 x_2 + \theta = 0 \quad (5)$$

The single layer network represents a linear discriminant function. So if the input neuron is *–i* th and output neuron are *–j* th, the equation can be:

$$y_i = F(\sum_{i=1}^{n} w_{ij} x_i + \theta_i) \qquad (6)$$

The training procedure of a BP network is iterative, with the weights adjusted after the presentation of each case [13]. It is because there are multiple layer, the input of a unit *j* may be the output of a unit in the previous layer, x_i. The input of a unit *j* is the sum of the bias of the unit, θ_i and the weighted sum of all the outputs of the units connected to unit *j*.

$$y_j = F(\sum_{i=1}^{n} w_i x_i + \theta_j) \qquad (7)$$

The activation function of each output or hidden node is computed by applying a logistic function to the output, y of unit j. the output is the actual value of the logistic function:

$$y_j = \frac{1}{1 - e^{-yj}} \qquad (8)$$

In training mode, after the network computes its output, the weights are adjusted. This adjustment is proportional to the product of the learning rate and the error derivative, Figure 4 shows the BP neural network. This relationship can be represented with formula (9).

$$w_{ij(new)} = w_{ij(old)} + \beta (errdrv)_i x_j \qquad (9)$$

In Figure 3, the original image of 8-bits are extracted out and formed into 8 bit-planes ranging from bit-plane 0 until bit-plane 7. Each bit-plane is then fed into the neural network for verification. The recognition performances are then analyzed. Higher recognition rates are expected for higher order bit levels since most image information present here. On the other hand, lower recognition rate is expected for lower order bit levels because they contain only subtle image information.

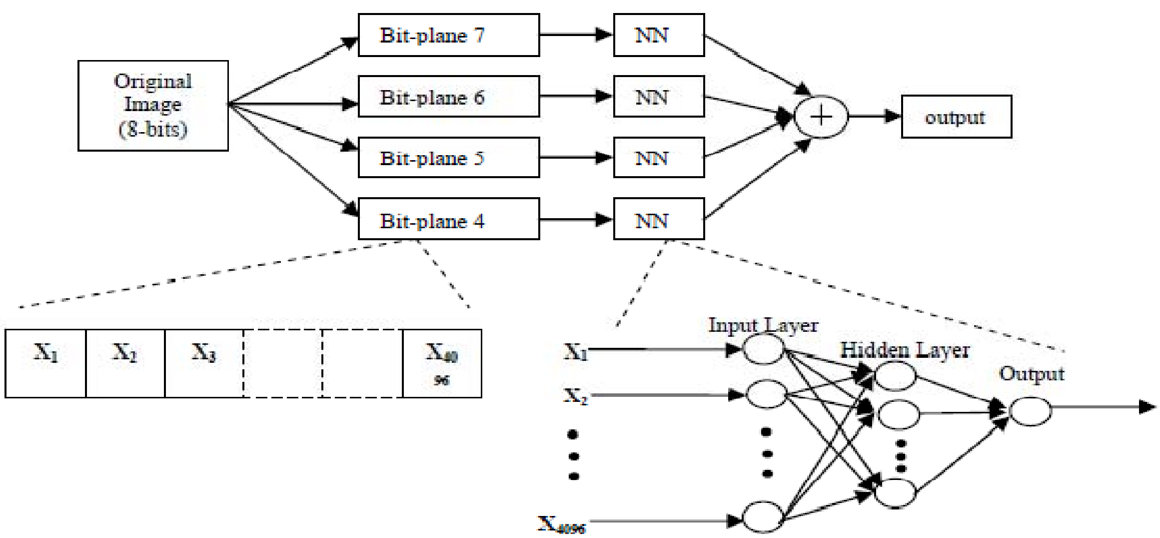

Figure 4. Back-Propagation Networks

III. Experiment Results

The performance of the thumbprint recognition in different bit levels is evaluated via its accuracy rate as shown in Figure 5. In this project, the database applied provides only 8 samples of image in each subject. Thus, only 4 samples are used to train the network.

From the result obtained, it is observed that lower order bit level (bit level 1- 4) shows lower percentage of recognition compared to higher order bit level (bit 5-8). Figure 5 shows that the highest accuracy rate is bit 6 with almost 60%. However, there’s a drastic drop in percentage for bit level 8 which is less than 10%.

Also, Figure 5 illustrates the result where all images in the database are tested with the network. In other words, untrained data is included into the system. As for Figure 6, all trained data are tested with the network. By comparing both graph, all trained data provides the best performance in the average accuracy. However, both still shows a low percentage of accuracy for bit level 8. This may due to the limitation of database used in this system. The more data trained, the better the performance the network is.

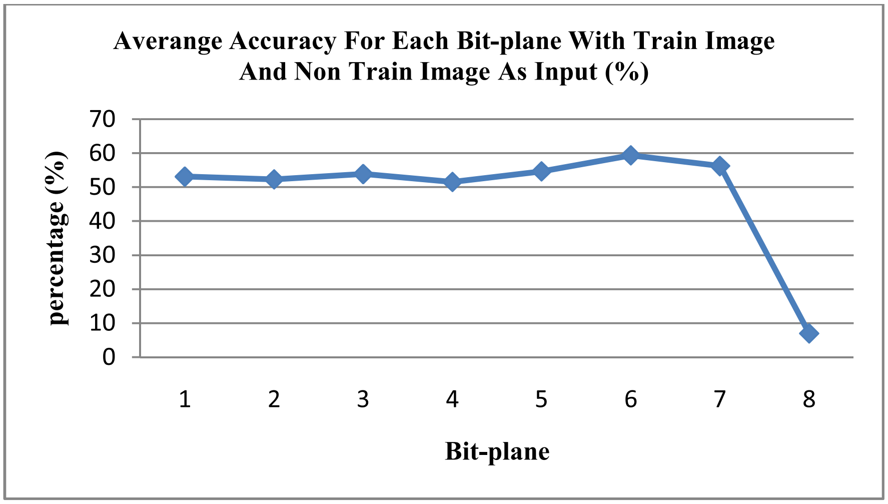

Figure 5: Accuracy of Neural Networks with Training Samples and Non-Train Image As Input

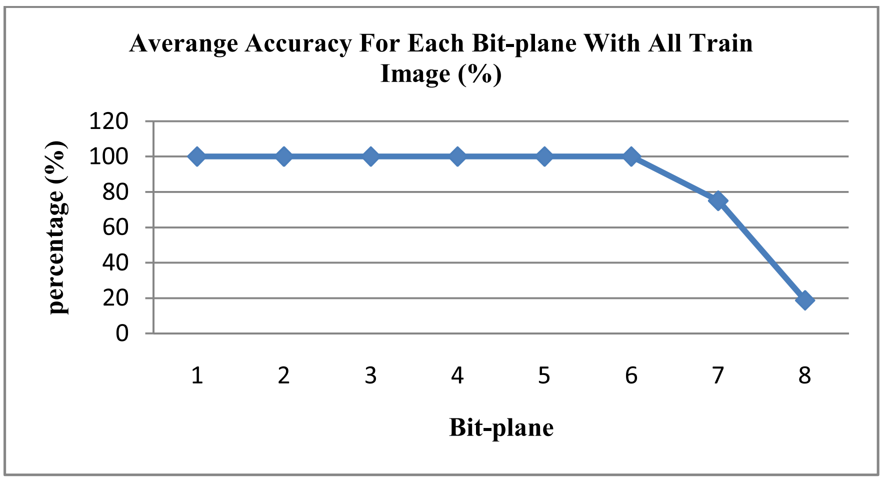

Figure 6: Accuracy of Neural Networks with All Training Samples Image as Input

IV. CONCLUSIONS

In conclusion, thumbprint recognition in neural network using bit planes were analyzed on different bit levels and the recognition rates are studied. The results showed an interesting recognition trend that was reduced drastically at the higher side of the bit levels. A more detailed analysis shall be performed with comprehensive database to study the correlation of the thumbprint recognition rates and bit levels.

ACKNOWLEDGMENT

The authors would like to acknowledge Ministry of Higher Education, Malaysia for the provision of research grant FRGS/03(03)/771/2010(52) and Faculty of Engineering, Universiti Malaysia Sarawak for the provision of research facilities

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