Palm Vein Recognition System using Directional Coding and Back-propagation Neural Network

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***Abstract*— This paper proposes an effective palm vein recognition system by using back-propagation neural networks for biometric application. In the recent years, because of the high development cost, vein pattern is not popular biometric as compared to other biometric system like fingerprint, palm print, face and iris. But, the advantage of palm vein on classical biometric are the low risk of falsification, uniqueness, strong immunity to forge and stability. Biometric palm vein images are acquired using near infrared illuminated LEDs and IR-Sensitive webcamera from 40 persons of different gender and ages. Firstly, the palm vein region of interest (ROI) was extracted from hand images; gamma correction and local ridge enhancement (LRE) were applied to the 100 x 100 pixels image and palm vein pattern images in order to obtain the correct contrast and sharpness of the image without excessively increasing the noise. The palm vein features were extracted from the enhanced region of interest for each sample using Sobel directional coding scheme in the four directions. The extracted Sobel images were converted to gray-scale image using Otsu's thresholding method. The resulting gray-scale image were divided into 20x20 sub-region before the feature matching. Mean absolute deviation (MAD) is implemented to these sub-region as the feature vectors. Those feature sets are the input on the back-propagation neural network. According to the results, the feature matching method can achieve up to 98.75% of correct classification rates.**

***Index Terms*— Biometrics, Palm Vein Recognition System, Neural Network, Sobel Directional Coding**

I. Introduction

In today's computer technology, there are many number of states which require an individual, as a user, to be confirmed by an electronic device. The traditional way that user can be verified is based on whether he/she is in possession of specific information which only she himself/herself is expected to know such as a pin or a password ("something that he/she knows") and/or whether he/she is in control of a certain token used as Smart Card or RFID Card ("something that she has"). These methods have a number of substantial drawbacks. Passwords may be forgotten or compromised. Token may be lost, stolen, misplaced, forged, or forgotten. Therefore, knowledge or token-based authentication does not provide enough safety in many application involving access control and financial transaction [1]. Biometrics-based personal identification system is developing as a dominant means for identifying a person's uniqueness with a high assurance. Among the many biometric features that can be used for personal authentication, the oldest and most effective form among all the biometric characteristics, is the hand. The features that could be extracted from the human hand includes knuckle print, fingerprint, palm print, palm vein, and hand geometry [2].

This study intent to investigate more in the development of the image acquisition that would minimize the hygiene concerns and psychological persistence. Thereby, the proposed system will be contactless in order ease of the hygiene concerns. Also, the study can be used as part of the access control unit. This access control unit controls access to rooms or building that are for restricted personnel.

The remainder of this paper is organized as follows. In the next section the authors present the review of literature on preprocessing, feature extraction and feature matching on palm vein recognition system. The proposed palm vein recognition is described in Section 3. In Section 4 we present some experimental results. In Section 5 we present the evaluation and comparison between hamming distance and neural network. Finally, conclusion and recommendations are discussed in Section 6.

Manuscript received July 21, 2015; revised August 5, 2015. This work was a graduate research paper at Mapua Institute of Technology with the financial support of Department of Science and Technology – Engineering Research and Development for Technology (DOST-ERDT)

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II. REVIEW OF RELATED LITERATURE

A. *Image Acquisition*

Due to body composition of human and using infrared light, the palm vein patterns of the hands can be easily observed. The infrared light is in between the visible and microwave of the electromagnetic spectrum. The typical wavelength of the infrared light is ranging from 0.75μm to 1000μm. Based on ISO 20473, the region of the infrared is divided into three sub-regions, far infrared with the range of 50-1000"μm" , mid infrared from 3"μm" up to 50"μm" and near infrared from 0.78"μm" up to 3"μm" . There are two types of infrared imaging technologies for palm vein authentication, far-infrared thermography and near-infrared imaging were analyzed in [3].

B. *Preprocessing*

In [4], the researchers proposed and used histogram equalization for vein image enhancement. This method is useful if the researcher uses FIR imaging technique, since

ISBN: 978-988-14047-2-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

this method redistributed the pixel intensity thus changing the sharpness and contrast of image. In year 2013, first extract the region of interest, and followed by noise removal by applying 5x5 filter on the region of interest in order to lessen the noise. To extract the brightness of image, Gaussian low pass 51x51 filter was applied to the region of interest that measured as a low frequencies and it was subtracted to the original region of interest. They apply normalization method because the image contrast is still too bad [5].

C. Feature Extraction

Global-based and structural methods are the two extraction methods for palm vein recognition. The feature points and line of the palm vein are used to by those important methods. In [4], the researchers used Gabor filter and Fisher Discriminant Analysis (FDA) for feature extraction. The region of interest were improved and extract using Gabor filter. To decrease the dimension of the array of features, the Fisher Discriminant Analysis have been used.

In [7], palm vein recognition system was developed using Hybrid Principal Component Analysis (PCA) for the feature extraction and Artificial Neural Network for clustering the data. The PCA-ANN experiments were considered twice when inputs to ANN were unscaled.

D. Feature Matching

In [6], the researchers used the most common algorithm to match the two images which is called cross-correlation algorithm. The correlation operation is linear and shift invariant. The similarity between the template image and testing image is calculated by measure the absolute difference between values in the test image and template images.

In the study of [7], the researchers used artificial neural network specifically the Self-organizing Feature Maps (SOFM) to clustering the tasks. The objective of clustering is to decrease the amount of data by classifying or grouping similar data items together. SOFM composed of two layers of units: an input layer and a competition layer (2013).

E. False Acceptance Rate – False Rejected Rate

False Acceptance Rate and False Rejection Rate are used to test the total success rate of the system. FAR is the ratio of the number of successful independent impostor tries against a person and number of all independent impostor tries against a person. An impostor attempt is successful when the graphical user interface gives an "access/successful" message. FRR is the ratio of the number of rejected authentication tries for a genuine person over to the number of all authentication tries for a genuine person. A verification attempt counts as rejected if the graphical user interface gives a "rejected/unsuccessful" message.

III. METHODOLOGY

This section describe the method and materials used in attaining the objectives of the study. Figure 1 illustrates the procedural steps. Explanations are provided in the discussion that follow.

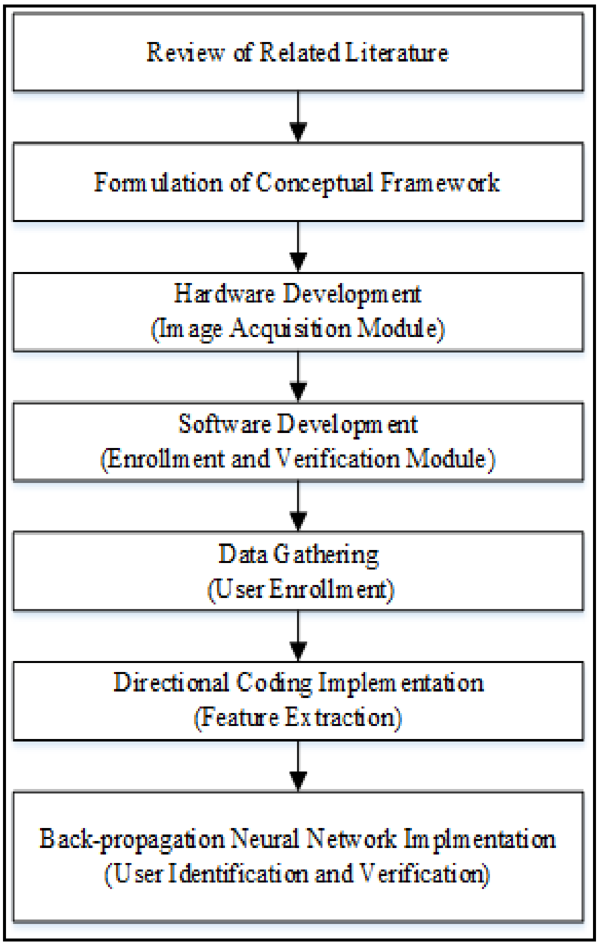

Fig. 1. Methodology

The first step involved a review of the literature related to the study to conceptualize and develop the system. The problem statement and the conceptual framework were then formulated, the selection of materials needed in the development of the modules was done. The development of the hardware design came third, followed by the development of the software design. The fifth step involved the gathering of data from the right hand of the 40 persons as test subjects. In the sixth step, the gathered data or images were process to extract the important features using Directional Coding. The seventh and final steps involved identification and recognition of the user that are registered in the system using Back-propagation Neural Network.

Figure 2 shows the block diagram of the hardware and software components which is composed of four components: image acquisition module, enrollment module, template database, verification module. The acquisition stage is responsible for acquiring palm vein images of a user who tends to access the system.

The template database is a collection of data which contain all the information of all the users who enrolled in the system. The verification module is responsible for locating the ROI, feature extraction, feature matching. Also, it is responsible for classifying if the subject/user is a "genuine user" (the claimed identity is "verified") or an "impostor".

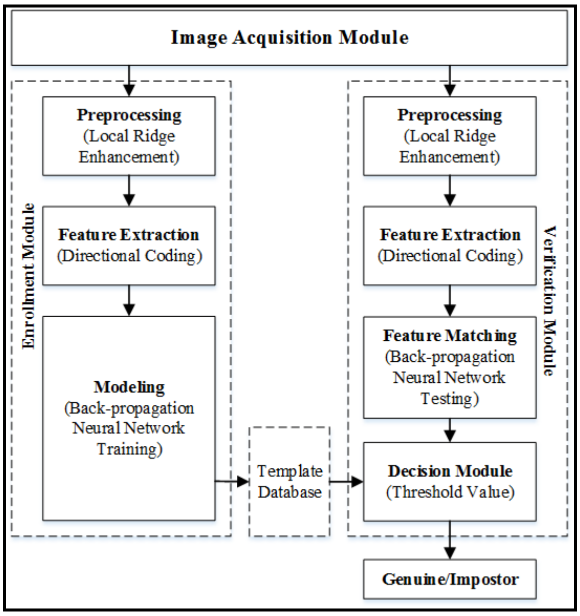

Fig. 2. Block Diagram of Palm Vein Recognition System

A. *Image Acquisition Module*

Image acquisition plays a precise significant role because it produces the biometric images to be evaluated and used in this study. The researchers developed an acquisition device which can capture palm vein image. There are many challenges to be taken into consideration in scheme and implementation of the image acquisition device. Firstly, since this study involve vascular pattern, an acquisition device must be used to capture vein patterns. However, it is not economical to used high-cost FIR or NIR camera to obtain IR images, since there are many techniques involve in the enhancement of the palm vein patterns during the processed of preprocessing and feature extraction. Therefore, a low to medium development cost for acquisition device is expected for palm vein recognition system. Secondly, the acquisition device must produce good images so that the vein features can be observable enough to be used for processing. The prototype implementation plays a critical role in providing excellent palm vein images. Also, the design of the infrared lights and arrangement of the imaging device have great influence in providing high quality vein pattern.

During registration or verification, the user will place his/her hand above the camera. The system will automatically detect the contour line of the hand and the region of interest. The user must place his hand 25-30cm away from the camera. After the hand was detected, the region of interest of the palm vein will be captured and the result will be displayed in the LCD. The break between capturing the current and the next region of interest could be approximately 2-5 seconds.

B. *Enrollment Module*

During the enrollment, the extracted template are stored in the database and were used in the matching process as database template. Also, the captured biometric images will underwent pre-processing and feature extraction, before it will be stored in the database. The researchers used MS SQL Database as the database of the system. The system was tested on 40 person's palm vein images that are registered in the database. This image database consists of 400 gray-scaled right hand palm vein images (10 images per person).

C. *Verification Module*

There are distinctive features in a palm vein image that can be used for personal recognition and identification. The useful features for palm vein are the wrinkles, principal lines, and ridges. Lines and texture features can be observed in palm vein images.

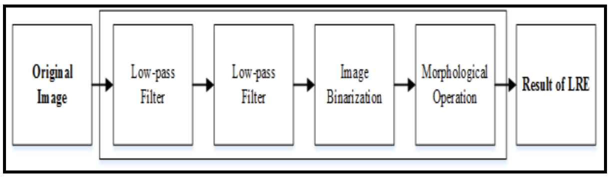

Fig. 3. Local Ridge Enhancement Block Diagram

Preprocessing

After obtaining the region of interest, palm vein features were highlighted by enhancing the sharpness and contrast of the images and become separable from the background. The researchers used the method of [2] algorithm to get a sharp image without excessively increasing the noise.

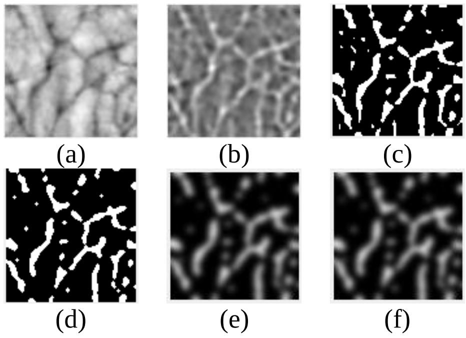

Fig. 4 Preprocessing Results.

The algorithm is termed as local ridge enhancement that finds the palm vein details by using ridge detection mask. The steps in the LRE as showed in Figure 3 are:

1. Local-ridge-enhancement put on a low-pass filter, lp, on the original image, $V(x,y)$ to obtain a blur form of the image, $B(x,y)$.
   $$B(x,y) = lp(x,y) * V(x,y) \tag{1}$$
2. Applying a Laplacian filter on the output of blur image. To trace the ridge edges the Laplacian high-pass $hp(x,y)$ filter have been used, as shown in Figure 4.a.
   $$B'(x,y) = hp(x,y) * B(x,y) \tag{2}$$
3. $B'(x,y)$ shows the edges of the principal ridge structure. The image was binarize $B'(x,y)$ by using Otsu's thresholding method. Morphological opening operator (Figure 4.c.) have been used followed by morphological closing operator (Figure 4.d.) that eliminate undesirable noise regions. The output image (Figure 4.e.) is the "mask" marking the position of the string ridge pattern. Overlay $B'(x,y)$ on the enhanced image to intensify the edge region.
   $$V'(x,y) = \begin{Bmatrix} k \cdot V(x,y) & \text{if } B'(x,y) = 1, \\ V(x,y) & \text{otherwise} \end{Bmatrix} \tag{3}$$

ISBN: 978-988-14047-2-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

where $V'(x,y)$the enhanced image k is the constant to regulate the level of strength used to get the best part of the ridge area.

Feature Extraction

This method will extract the palm vein of the human hands. The method is similar to the method described in [2]. The algorithm named Sobel Directional Coding to extract the discriminative information from palm vein. Since palm vein is consist of vascular system that looks like line representation. The steps for the feature extraction scheme:

1. Sobel operator have been used to identify the palm vein directions in $0°$, $+45°$, $90°$, and $135°$ degrees; Four-directional operators Sobel_0, Sobel_{90}, Sobel_{45}, and Sobel_{135}.

2. Then the resultant sample,$\emptyset(x,y)$,

$$\emptyset(x,y) = \delta(\arg max_f(\omega_R(x,y)) \quad (4)$$

$$\emptyset(x,y) = \max\begin{pmatrix} f * Sobel_0, f * Sobel_{45}, \\ f * Sobel_{90}, f * Sobel_{135} \end{pmatrix} \quad (5)$$

where the symbol * is refers as the convolution operator, and $\omega_R(x,y)$ represents the results of the Sobel mask in the four directions ($0°$, $45°$, $90°$, and $135°$), and $\delta \in \{0,45,90,135\}$ indicates the index to code the orientation of. The output, $\emptyset(x,y)$, is a bit arrays, will be converted to the corresponding array of binary output.

The resultant maximum gradient descent Sobel image was encoded using mean absolute deviation (MAD) algorithm. The 100 x 100 pixels resolution palm vein images were divided to 20 x 20 pixel sub-images and mean absolute deviation was implemented to each sub-images. The obtained feature array has a length of 5*5 = 25 bytes. The feature arrays were applied to the back-propagation neural network as an input for classification of the palm vein images.

Feature Matching

In the algorithm, the recognition of palm vein pattern images is achieved by using back-propagation neural network. The systematic step-by-step procedure is called a neural network that have a variable known as the learning rule which optimizes the network. The basic building block of a neural network is a neuron. The basic neuron is consist of a box with weighted inputs and an output.

In this study, the researchers used three most useful training protocol for back-propagation algorithm. These are stochastic neural network, on-line neural network, batch neural network. The training patterns of theses neural network are randomly chosen from the training set and the network weights will be update depending on the neural network. In stochastic neural network, the network weights are updated for each input presentation. In on-line training, each input is presented once and it doesn't need memory for storing the input. In batch training, all inputs are offered to the neural network earlier before learning the training proceeds.

IV. EXPERIMENT RESULTS

In this study, there are two evaluations and comparisons to test the performance of the palm vein recognition system:

1) Evaluate and compare the performance of three different learning algorithms of the back-propagation neural network.
2) Evaluate and compare the performance between hamming distance and best learning algorithm back-propagation neural network (previously evaluated) as the feature matching of the system.

In order to evaluate the performance based on the recognition rate of the system of the palm vein pattern feature arrays, learning based back-propagation neural network have been performed in this study. Three different learning algorithms have been used. These are stochastic back-propagation, online back-propagation, and batch back-propagation. Tangent hyperbolic transfer function was used as stimulation function. Mean square error (MSE) function was used for measuring the training correctness of the network. The selected value for MSE is 0.001. It determines how well the network output turns the target output. The neural network have: 25 (input feature array) - 40 neurons in the hidden layer - 40 neurons in the output layer.

For each test of the selected protocol, given the threshold value and a sample from both genuine users and imposters users we can create estimates for the false accepted rate (FAR) , false rejected rate (FRR), total success rate (TSR), correct classification rate (CCR) in the following way:

$$\mathrm{FAR} = \frac{\#(\mathrm{T} > \tau \mid \mathrm{T} \in \mathrm{Genuine})}{\#\mathrm{Genuine}} \text{ x } 100\% \quad (6)$$

$$\mathrm{FRR} = \frac{\#(\mathrm{T} \leq \tau \mid \mathrm{T} \in \mathrm{Impostor})}{\#\mathrm{Impostor}} \text{ x } 100\% \quad (7)$$

$$\mathrm{TSR} = \left(1 - \frac{\hat{\mathrm{p}}_{\mathrm{FAR}}\,(\%) + \hat{\mathrm{p}}_{\mathrm{FRR}}\,(\%)}{\text{Total number of access}}\right) \text{ x } 100 \quad (8)$$

$$\mathrm{p}_{\mathrm{CCR}} = \frac{\text{Number of sample pass in test}}{\text{Number of sample} * \text{Number of test}} \quad (9)$$

Where T is the matching score from sample, τ is the threshold value, and $\hat{p}_{FAR}$ and $\hat{p}_{FRR}$ are estimator for false accepted rate and false rejected rate, respectively.

TABLE I
EXPERIMENTAL RESULT OF FAR AND FRR (%) FOR STOCHASTIC BACK-PROPAGATION

Test #	Iteration	Threshold (τ)	False Acceptance Rate (FAR) (%)	False Rejected Rate (FRR) (%)	Total Success Rate (TSR) (%)
1	3433	0.37	1.25	3.75	97.5
2	3431	0.36	1.25	3.75	97.5
3	3439	0.35	1.25	3.75	97.5
4	3437	0.36	1.25	3.75	97.5
5	3433	0.36	1.25	3.75	97.5

Table I shows the result of the stochastic back-propagation. For each test, 80 random images have been selected from the database. The iteration for each test refers to the number of iteration for the stochastic back-propagation neural network to train the system. The false acceptance rate and false rejected rate with the corresponding threshold have been computed using (6) and (7), respectively. And the total success rate (TSR) of the system have been computed using (8).

Figure 5 shows the line graph of the percentage of the false acceptance rate and false rejected rate for stochastic back-propagation. The threshold value is the intersection of

ISBN: 978-988-14047-2-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

the FAR-FRR. In this figure, the threshold value is equal to 0.36. When the user's matching score is greater than the threshold value, the user will be considered as genuine otherwise they will considered as impostor.

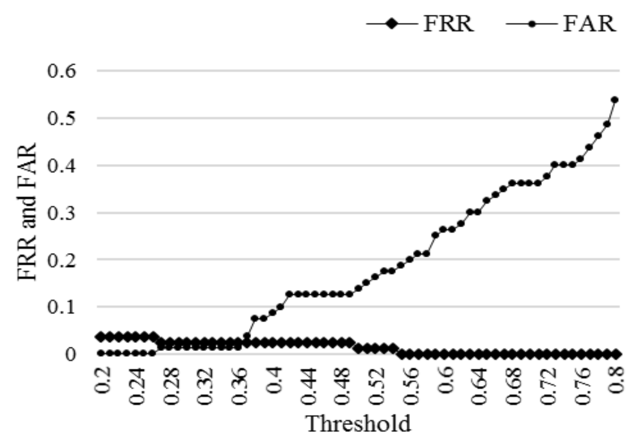

Fig. 5. FAR-FRR Diagram for Stochastic Back-propagation

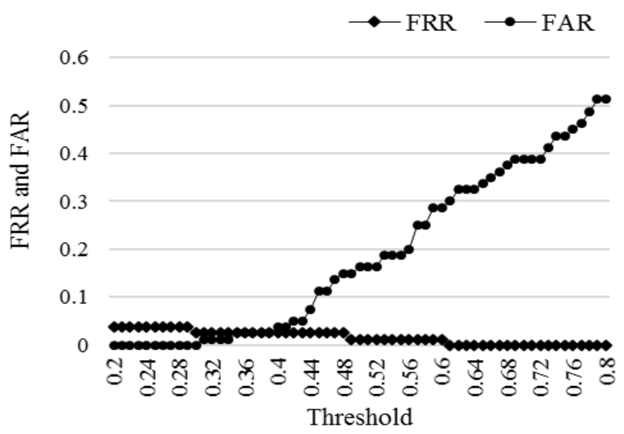

Fig. 6. FAR-FRR Diagram for Online Back-propagation

Figure 6 shows the line graph of the percentage of the false acceptance rate and false rejected rate for online back-propagation. The threshold value is the intersection of the FAR-FRR. In this figure, the threshold value is equal to 0.38. When the user's matching score is greater than the threshold value, the user will be considered as genuine otherwise they will considered as impostor

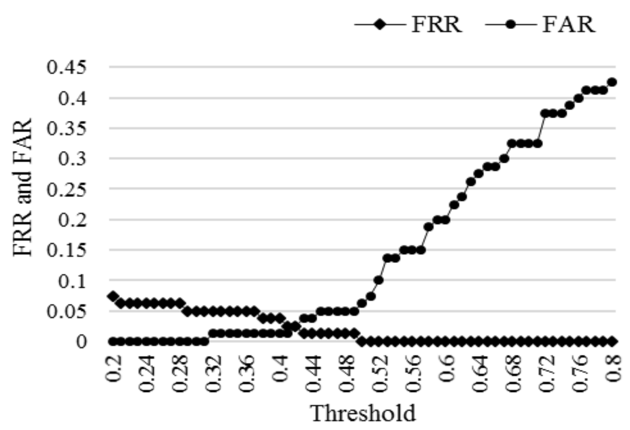

Fig. 7. FAR-FRR Diagram for Batch Back-propagation

Figure 7 shows the line graph of the percentage of the false acceptance rate and false rejected rate for batch back-propagation. The threshold value is the intersection of the FAR-FRR. In this figure, the threshold value is equal to 0.41. When the user's matching score is greater than the threshold value, the user will be considered as genuine otherwise they will considered as impostor.

TABLE II
OVERALL RESULT OF CCR (%)

Neural Network	# of Test	Total Number of Images used in Testing	Average Iteration	Average Time to train Palm Vein database (seconds)	CCR P_{CCR}(%)
Stochastic	10	80	3434	51.5	97.25
Online	10	80	5741	86.8	98.625
Batch	10	80	18604	923	98.625

Table II shows the average iteration from 10 tests and time to train each network. The probability of the CCR (%) have been computed using (9). The correct classification rate is defined as the correctness of the system to determine or classify whether a certain user is genuine or impostor.

TABLE III
COMPARISON OF EXPECTED COUNTS AND OBSERVED COUNTS FOR STOCHASTIC BACK-PROPAGATION

Test	Observed	Expected
1	78	73.11
2	78	73.11
3	78	73.11
4	78	73.11
5	78	73.11

Table III shows the observed counts and expected counts for stochastic back-propagation. The expected counts have been computed using (10).

The hypotheses for this study are as follows:

1) Null hypothesis: The system's number of successes on 10 tests for each protocol follows a binomial distribution.
2) Alternative hypothesis: At least one of the test in the null hypothesis is false.

TABLE IV
CHI-SQUARE RANDOM VARIABLES OF EACH BACK-PROPAGATION NEURAL NETWORK PROTOCOL

Back-propagation Neural Network	Chi-square random variable (χ^2)	Accepted Hypothesis
Stochastic	10.36624	Null hypothesis (H_0)
Online	0.338087	Null hypothesis (H_0)
Batch	0.338087	Null hypothesis (H_0)

Observation:

Based on the Chi-Square Distribution Table, using $df = 9$ and 0.05 as significance level, the value of chi-square variable is χ_c^2=16.919. Since the value of the chi-square random variable (χ^2) of each neural network protocol is less than the chi-square variable (χ_c^2), therefore there are no evidence against null hypothesis.

ISBN: 978-988-14047-2-5
ISSN: 2078-0958 (Print); ISSN: 2078-0966 (Online)

V. EVALUATION AND COMPARISON BETWEEN HAMMING DISTANCE AND NEURAL NETWORK

The researcher used one of the most common feature matching algorithm, the hamming distance, to know the effect of the absence of the back-propagation neural network in the recognition system. Also, to compare the performances between the two feature matching algorithm.

The hamming distance was used to tally the portion of bits that vary between two binary arrays from palm vein images. And is defined as,

$$d_{ham}(V1, V2) = XOR(V1, V2)$$
$$d_{ham}(V1, V2) = \frac{1}{S}\sum_{i=1}^{B} V1_i \bigotimes V2_i \quad (10)$$

Where $V1_i$ and $V2_i$ signify the i-th bit in the sequences $V1$ and $V2$ respectively, and S refers to the sequence number of bits. The $\otimes$ operator refers the exclusive OR operator. The template is shifted 8 bits to the right and left to obtain multiple hamming distances. The lowest distance is chosen.

Same test for the recognition system using hamming distance as feature matching algorithm. The 80 images were randomly selected from the database.

TABLE V
EXPERIMENTAL RESULT OF FAR AND FRR (%) FOR HAMMING DISTANCE

Test #	Total Number of Images used in Testing	False Acceptance Rate (FAR) (%)	False Rejected Rate (FRR) (%)	Total Success Rate (TSR) (%)
1	80	3.75	3.75	96.25
2	80	3.75	5	95.625
3	80	3.75	3.75	96.25
4	80	5	3.75	95.625
5	80	5	3.75	95.625

Table V shows the result of the hamming distance. For each test, 80 random images were selected from the database. The false acceptance rate FAR (%) and false rejected rate FRR (%) will be computed using (6) and (7), respectively, with the threshold (τ) of 0. 28. The threshold value have been determine where FAR and FRR meet. If the user matching score is less than threshold value, the user will be considered as genuine otherwise they will be considered as impostor.

The Correct Classification Rate (CCR) for feature matching algorithm: back-propagation neural networks and hamming distance. The expected CCR (%) of the back-propagation neural networks are higher than hamming distance. The figure shows that the correctness or accuracy of the palm vein recognition system is greater when back-propagation neural networks is used as feature matching algorithm.

VI. CONCLUSION AND RECOMMENDATION

In this paper, an effective palm vein recognition system is presented to authenticate individuals by using their palm vein features. The recognition system was developed using C# and MATLAB. The researchers used directional coding scheme to extract the feature of the palm veins and the resulting gray-scale image were divided into 20x20 sub images using mean absolute deviation (MAD) before feature matching.

Also, the researchers proposes three verification neural network mechanism to verify the palm vein images. In stochastic back-propagation, the network weights are reorganized for each input presentation. Using this method, the system can achieve above 97% correct classification rate. In on-line back-propagation, each input is presented once and it doesn't need memory for storing the input. Using this method, the system can achieve above 98% correct classification rate. In batch training, all inputs are offered to the neural network earlier before learning the training proceeds. Using this method, the system achieve above 98% correct classification rate. Stochastic back-propagation tends to be faster on training time but provides lower classification rate compare to two back-propagation neural network. Batch back-propagation have the highest classification rate but slower on training time.

Based on results and finding of the study the following are recommended for future improvement of the system:

1) The use of distance sensor to inform the user about the distance of his/her hand from the imaging acquisition device.
2) Improvement on the hand tracking and region of interest detection algorithm.
3) The use of IR-sensitive camera to provide high quality image to lessen the enhancement process of the region of interest that will make the system faster on feature extraction.
4) The extraction and verification using both hands.

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