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Palm Vein Recognition System Using Hybrid Principal Component Analysis and Artificial Neural Network

Omidiora Elijah Olusayo, Oladosu John Babalola, Ismaila Wasiu Oladimeji
Department of Computer Science and Engineering,
Ladoke Akintola University of Technology,
Ogbomoso, Nigeria

Agbaje K. M., Adeniyi A. Yusuf
College of Science,
Engineering and Technology,
Osun State University,
Oshogbo, Nigeria

Abstract: Palm vein recognition is one of the most desirable biometric identification techniques. Several researches have been carried out on palm vein which has led to the proposition of different techniques. This research work focuses on palm vein recognition system using Hybrid Principal Component Analysis (PCA) and Self Organizing Map (SOM). The PCA-ANN experiments were considered twice when inputs to ANN were unscaled (raw scale between 0 and 255) and scaled (scale between 0 and 0.9). The performance of the system was evaluated based on different image resolutions, different training datasets, recognition time and recognition accuracy. The unscaled PCA-ANN and scaled PCA-ANN gave an optimal recognition accuracies of between (55% and 98%) and (56%-99%) respectively at a resolution of between 30*30 and 60*60 pixels level of cropping. Also further experiments were performed in determining the error rates so that the scalability of the algorithms to the task of controlling access will be investigated. The FAR and FRR were between (2.5%-12.5% for unscaled and 2.5-15% for scaled) and (2%-82% for Unscaled and 1%-81% for scaled) at 0.0001 threshold respectively. EER was 9.839% for unscaled PCA-ANN at 49.53 pixels resolution and 12.53% for the scaled PCA-ANN at 46.37 pixels resolution. This showed that EER was achieved at lower pixels resolution (46.37) for scaled PCA-ANN than the unscaled PCA-ANN (49.53) which revealed that overall system accuracy would optimally be attained by scaled PCA-ANN than the unscaled PCA-ANN.

1. INTRODUCTION

Palm vein authentication is one of the vascular pattern authentication technologies. Vascular pattern authentication includes vein pattern authentication using the vein patterns of the palm, back of the hand or fingers as personal identification data, and retina recognition using the vascular patterns at the back of the eye as personal identification. Since everyone has vessels, vascular pattern authentication can be applied to almost all people. If vascular patterns were compared to the features used in other biometric authentication technologies, such as the face, iris, fingerprint, voice, and so on, the only difference would be whether or not the feature is at the surface of the body. Consequently, vascular patterns cannot be stolen by photographing, tracing, or recording them. This means that forgery would be extremely difficult under ordinary conditions [6, 7]. Palm vein authentication has a high level of authentication accuracy due to the uniqueness and complexity of vein patterns of the palm. The palm vein patterns are internal to the body; which makes it difficult to forge. Also, the technology is hygienic for use in public areas. It is more powerful than other biometric authentication such as face, iris, and retinal. Palm vein authentication uses an infrared beam to penetrate the users hand as it is held over the sensor; the veins within the palm of the user are returned as black lines [3].

Principal Components Analysis which is one of the independent techniques used in this research work (PCA) is an analytical tool used in identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences. Since in high dimension data it is hard to find patterns, where the luxury of graphical representation is not available PCA is a powerful tool for analyzing data. Once patterns have been extracted from the data, and one needs to compress the data (i.e. by reducing the number of dimensions) without much loss of information, PCA is a good choice for it. In terms of information theory the idea of using PCA is to extract the relevant information in a palm vein image, encode it as efficiently as possible and compare test palm vein encoding with a database of similarly encoded models. A simple approach to extract the information contained in an image of palm vein is to somehow capture the variations in a collection of palm vein images independent of judgment of features and use this information to 75 encode and compare individual palm veins

[5]. Also, Self-organizing feature maps (SOFM) also called Kohonen feature maps are a special kind of neural networks that can be used for clustering tasks. The goal of clustering is to reduce the amount of data by categorizing or grouping similar data items together. SOFM consists of two layers of neurons: an input layer and a so-called competition layer. The weights of the connections from the input neurons to a single neuron in the competition layer are interpreted as a reference vector in the input space. That is, a SOFM basically represents a set of vectors in the input space: one vector for each neuron in the competition layer [10]. This research work hybridized a dimension reduction technique i.e. PCA and an unsupervised neural network usually used for clustering data i.e. SOM together, so that an output of the PCA, is an input to the SOM algorithm.

2. Literature Review

A palm vein recognition system using multimodal features and Adaptive sequential floating forward search (ASFFS) neural network was developed by [1]. The effects of fusion of multiple features at various levels were demonstrated. The shape and texture features were considered for recognition of authenticated users and it was validated using adaptive sequential floating forward search. The recognition accuracy of the developed system was found to be 99.61% when the multimodal features fused at matching score level. The recognition system developed provides reliable security [1,2]. Yi-Bo et al, 2007 [11] developed a scheme for personal authentication using palm vein. The infrared palm images which contained the palm vein information were used for the system. The system provides personal authentication and liveness detection concurrently because the vein information represents the liveness of a human. The system was in three phases: Infrared palm images capture; Detection of Region of Interest and palm vein extraction by multi-scale filtering and matching. The experiment results demonstrated that the recognition rate using palm vein is good. In year 2007, Shi et al [8] proposed a biometric technique using hand-dorsa extracting vein structures. For conventional algorithm, it is necessary to use high-quality images, which demand high-priced collection devices. The proposed method makes use of a low-cost devices and able to extract vein image. The results showed that the low cost device could extract the vein pattern networks successfully as using high-quality images. In year 2005, Masaki et al [7] worked on a biometric authentication using contactless palm vein authentication device that uses blood vessel patterns as a personal identifying factor. Implementation of these contactless identification systems enables applications in public places or in environments where hygiene standards are required, such as in medical applications. In addition, sufficient consideration was given to individuals who are reluctant to come into direct contact with publicly used devices. Toshiyuki and Kubo, 2004 [9] proposed a certification system that compared vein images for low-cost, high speed and high-precision certification. The equipment for authentication consists of a near infrared light source and a monochrome CCD to produce contrast-enhanced images of the subcutaneous veins. It adopted phase only correlation and template matching as a recognition algorithm. It was tested on several noise-reduction filters, sharpness filters and histogram manipulations which eventually produced best effort.

The application of vein detection concept to automate the drug delivery process was studied by [4]. The experiment deals with extracting palm dorsal vein structures, which was a key procedure for selecting the optimal drug needle insertion point. Gray scale images obtained from a low cost IR-webcam are poor in contrast, and usually noisy which make an effective vein segmentation a great challenge. Here a new vein image segmentation method was introduced, based on enhancement techniques resolves the conflict between poor contrast vein image and good quality image segmentation. Gaussian filter was used to remove the high frequency noise in the images. The ultimate goal was to identify venous bifurcations and determine the insertion point for the needle in between their branches was achieved. The theoretical foundation and difficulties of hand vein recognition was developed by [12]. The threshold segmentation method and thinning method of hand vein image were deeply studied. In addition, a new threshold segmentation method and an improved conditional thinning method were then proposed. The method of hand vein image feature extraction based on end points and crossing points were also studied, and the matching method based on distances was used to match vein images.

3. Methodology

An image can be viewed as a vector of pixels where the value of each entry in the vector is the gray scale values (0-255) of the corresponding pixel. For instance, an 8*8 image may be unwrapped and treated as a vector of length 64. The image is said to be in N-dimensional space, where N is the number of pixels (and the length of the vector). This vector representation of the image is considered to be the original space of the image.

3.1 Stages of Palm Vein Recognition System Development

The required stages involved in developing palm vein recognition are highlighted as follows:

STAGE1: Palm vein Acquisition

Data acquisition is the first stage of any pattern recognition process. It is the process that involves the sampling of biometric feature and the conversion of these features into the form that can be manipulated by the computer.

STAGE2: Palm Vein Preprocessing

This stage prepares the captured palm vein image for preprocessing. Preprocessing involves the following activities:

1) Scaling of Pictures Palm vein images were cropped from its original captured sizes and were later resized from the original dimension of 480*640 to 200*200 pixels.
2) Organizing the captured images into palm vein folder The resized images of each individual were grouped into two major folders. One folder contained training images while the other was used for testing the system. The folder

containing the training images were sub-divided into four (11) folders with each containing different resolutions of training images.

3) Cropping The images were cropped to sizes of 10*10, 15*15, 20*20, 25*25, 30*30, 35*35, 40*40, 45*45, 50*50, 55*55 and 60*60 pixels from the centre of the image by the program in order to test for the effect of varying resolution on the recognition performance.
4) Gray Scale Conversion The cropped images in the database were converted into gray scale so as to make it suitable for the palm vein recognition system. This was done because most of the present palm vein recognition algorithms require two-dimension arrays in their analysis.

STAGE3: Feature extraction This is the process of using the most important information of the cropped palm vein images for classification purpose. PCA algorithm was used to extract sufficient features (like principal lines, wrinkles, delta points and minutiae) that enhanced the recognition rate as shown in figure 1.

STAGE4: Training and Classification Computed eigenpalms (eigenvectors) were ordered at this stage to form eigenspace. The centered training image vectors were then projected onto the eigenpalm space. Euclidean distance was used as a threshold to determine the class, the training and the testing image belong.

STAGE5: Recognition/Testing Testing and recognition were performed using different image resolution and different training images per individual to determine performances under different image sizes as depicted in figure 2.

In this work, a hybridized a dimensional reduction technique (PCA) and an unsupervised neural network usually used for clustering data (SOM) was developed, so that the output of the PCA would serve as input to the SOM algorithm as illustrated in figures 1 and 2 below.

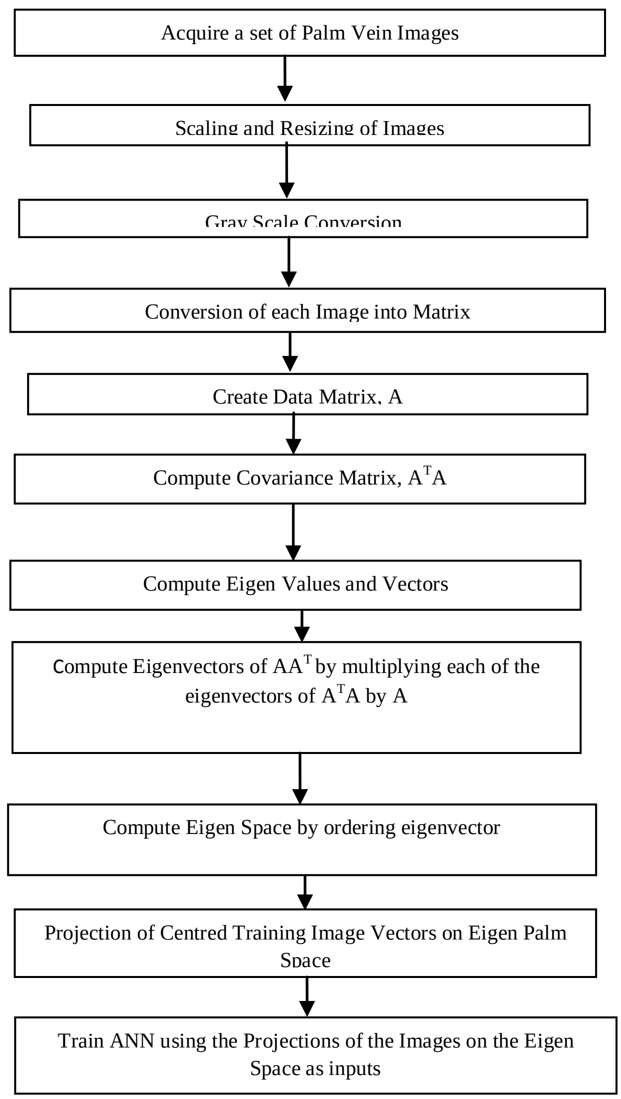

Fig.1 The Processes involved in the Training Stage of a Palm Vein Recognition System using Hybrid PCA and ANN

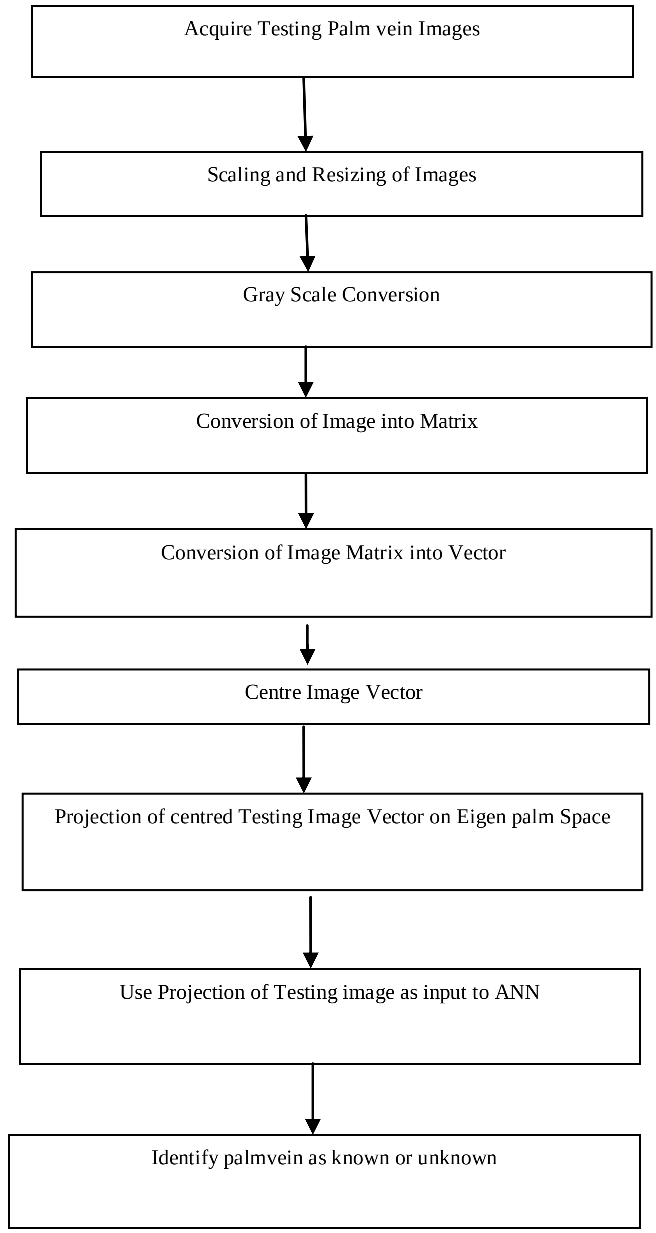

Fig.2 The Processes involved in the Testing Stage of a Palm Vein Recognition System using Hybrid PCA and ANN

4. Experiments

The code implementing the palm vein recognition system was tested on a dual core system board with 2.2GHz processor speed. The experimental results got were basically limited by the medium level state of the computer system, palm vein scanner, different environmental conditions, and the quality of palm vein images. The palm vein database under consideration was developed entirely from the scratch and the facilities for proper palm vein alignment used were the ones at our disposal. The palm vein recognition system was experimented with a total of 160 images, out of which 140 images were used in training the database and 100 images were used for testing the created database. This represents six images (four training and two testing) for 40 individuals representing a class each.

The experiment performed in this research work was sectioned in two namely:

Experiment 1

i. Unscaling the Input to the ANN

The raw inputs to ANN were unscaled between 0 and 255; all other projection values were then made to fall between the ranges.

Experiment 2

i. Scaling of Input to the ANN

Inputs to the ANN were re-scaled to between 0 and 0.9 against the wide range interval of between 0 and 255. This was achieved using formula below:

New_value=((0.9-0.1)*Old_value/(Amax-Amin))+(0.9-(0.9-0.1)*Amax-Amin)),

Where, Amax and Amin are the maximum and minimum values within the projection of all images.

5. Results and Discussion

Experiments were conducted with image resolutions of between 10*10 and 60*60 pixel resolutions using both Unscaled and Scaled hybridized PCA-ANN algorithms. The results of experiment using both algorithms are as shown in Tables 1 to 4.

Experiments conducted with the systems revealed that the training time for scaled PCA-ANN is fairly more than that of the unscaled PCA-ANN because scaled PCA-ANN is computationally complex than the unscaled PCA-ANN. Furthermore, the total number of unidentified images fairly reduces as the pixel resolution increases. This is on the ground that the more the palm vein features that are included in the training and testing images, the better the recognition performance. The palm vein features involved include; principal lines, wrinkles, delta points and minutiae .Also, experiments conducted revealed that percentage recognition accuracy increase for the scaled PCA-ANN (19% and 99%) than the unscaled PCA-ANN (18% and 98%) due to its classification strength. The difference in percentage recognition accuracies from unscaled PCA-ANN to scaled PCA-ANN was 0.01% to 0.04% respectively. It was established from the results that for training and classification at every considered resolution, the performance goal of the neural network were met, which gave rise to reasonable percentage recognition accuracy.

In addition, further experiments were performed to determine the error rate for every resolution considered. This was done to investigate the scalability of the developed system in controlling access. The palm vein images that were used for the false acceptance rate were not part of the training set and were tagged imposters while those used for the false rejection rate (FRR) were those included in the training set of the developed system. Equal Error Rate (EER) which is used to represent the overall system accuracy, the resistance of the system to break-ins and the ability to match templates from authorized users were also investigated. The FAR and FRR were between (2.5%-12.5% for unscaled and 2.5-15% for scaled) and (2%-82% for Unscaled and 1%-81%) at 0.0001 threshold respectively as shown in tables 3 and 4. EER was 9.839% for unscaled PCA-ANN at 49.53 pixel resolution and 12.53% for the scaled PCA-ANN at 46.37 pixel resolution. This showed that EER was achieved at lower pixels resolution (46.37) for scaled PCA-ANN than the unscaled PCA-ANN (49.53) which revealed that overall system accuracy would optimally be attained by scaled PCA-ANN than the unscaled PCA-ANN.

Table 1: Parameters Considered for the Palm Vein Recognition System using Unscaled PCA-ANN

Resolution of Cropped Palm Vein Image	Total Number of Images used in Testing	Number of Unidentified Image	Time to train Palm Vein database (seconds)	Time to identify an image as known or Unknown (seconds)	Percentage Recognitio n rate (%)
10*10	100	82	69.652	4.456	18
15*15	100	73	75.208	5.403	27
20*20	100	64	93.097	5.620	36
25*25	100	55	124.145	6.320	45
30*30	100	45	168.541	7.780	55
35*35	100	36	225.809	8.405	64
40*40	100	27	287.381	10.391	73
45*45	100	18	322.567	12.054	82
50*50	100	9	380.004	13.386	91
55*55	100	6	470.696	15.243	94
60*60	100	2	626.521	44.640	98

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Table 2: Parameters Considered for the Palm Vein Recognition System using scaled PCA-ANN

Resolution of Cropped Face Image	Total Number of Images used in Testing	Number of Unidentified Image	Time to train Palm Vein database (seconds)	Time to identify an image as known or Unknown (seconds)	Percentage Recognition rate (%)
10*10	100	81	70.700	4.577	19
15*15	100	72	76.678	5.337	28
20* 20	100	62	96.841	5.545	38
25*25	100	53	126.516	6.310	47
30*30	100	44	169.006	7.221	56
35*35	100	34	226.235	8.681	66
40*40	100	25	289.500	9.915	75
45*45	100	15	335.133	13.070	85
50*50	100	6	426.585	13.171	94
55*55	100	2	482.634	14.809	98
60*60	100	1	627.479	17.630	99

Table 3: The False Acceptance Rate and False Rejection Rate of the Unscaled PCA-ANN at an Euclidean distance of 0.0001

Resolution of Cropped Palm Vein Image	%FRR	%FAR
10*10	82	2.5
15*15	73	2.5
20* 20	64	5
25*25	55	5
30*30	45	7.5
35*35	36	7.5
40*40	27	7.5
45*45	18	10
50*50	9	10
55*55	6	12.5
60*60	2	12.5

Table 4: The False Acceptance Rate and False Rejection Rate of the Scaled PCA-ANN at an Euclidean distance of 0.0001

Resolution of Cropped Face Image	%FRR	%FAR
10*10	81	2.5
15*15	72	5
20* 20	62	5
25*25	53	7.5
30*30	44	7.5
35*35	34	10
40*40	25	10
45*45	15	12.5
50*50	6	12.5
55*55	2	12.5
60*60	1	15

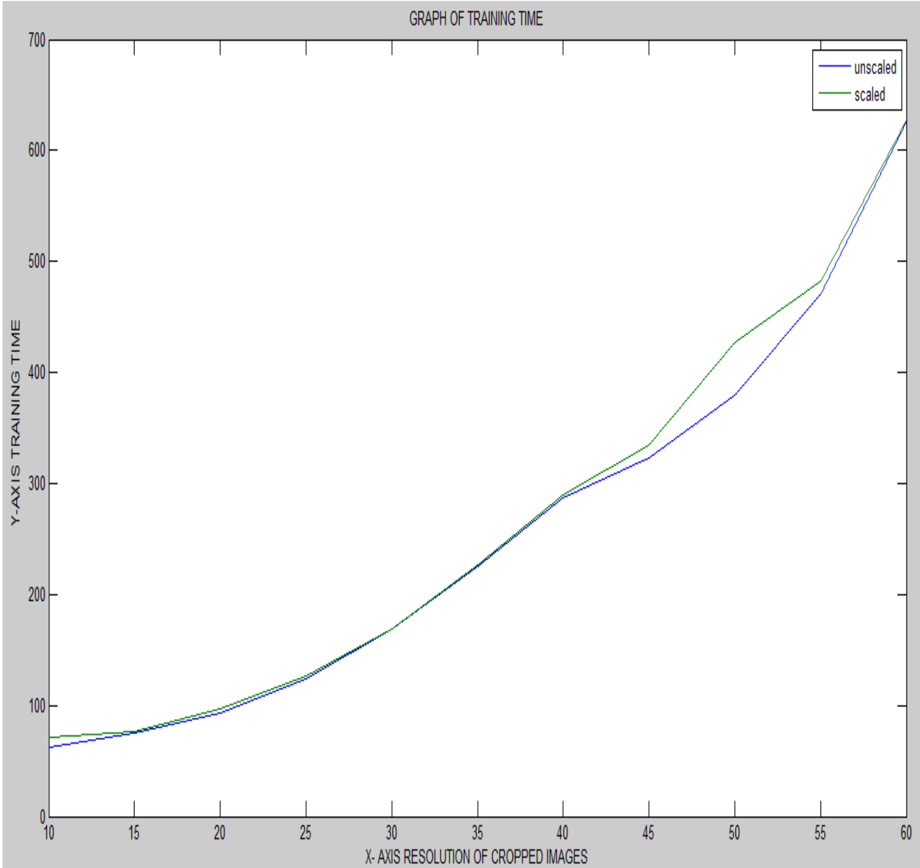

Fig. 3: Time used in Training Palm Vein at different Resolution of Cropped Image

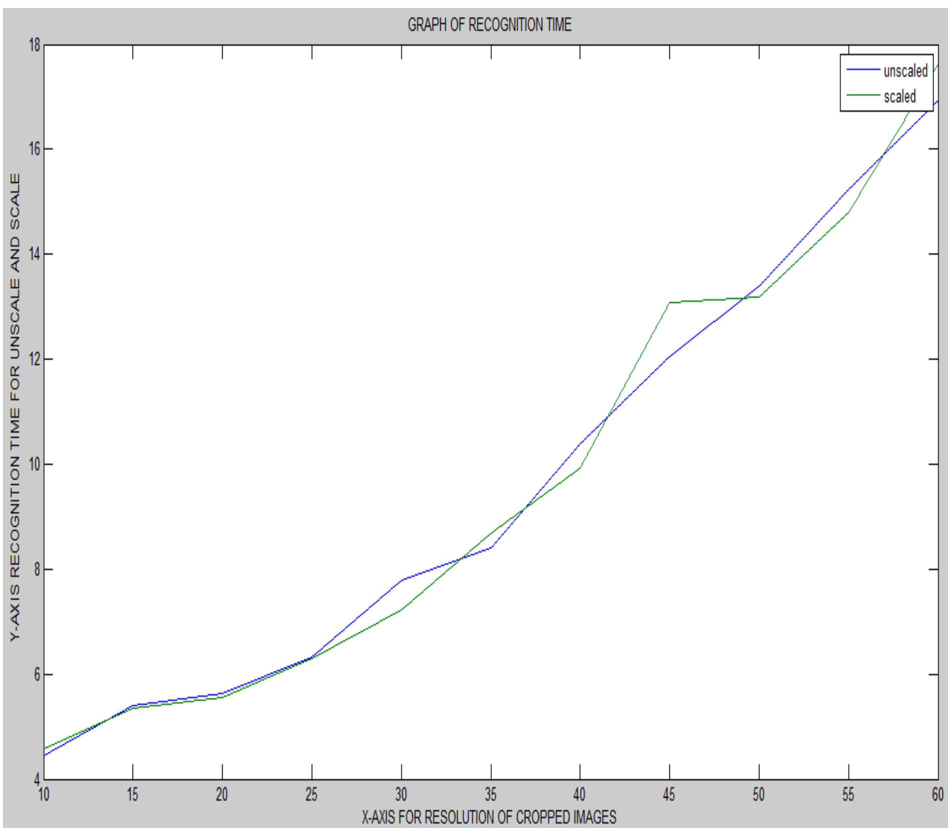

Fig. 4: Time to Recognized Palm Vein Image as known or Unknown

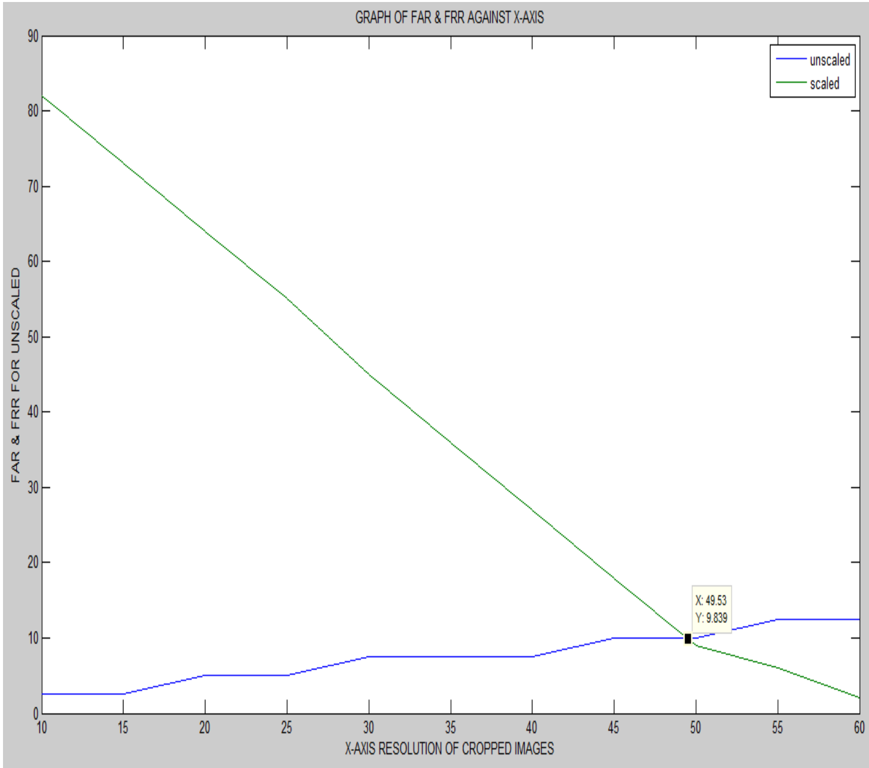

Fig. 5: False Acceptance Rate (FAR) and False Rejection Rate (FRR) for Unscaled PCA-ANN

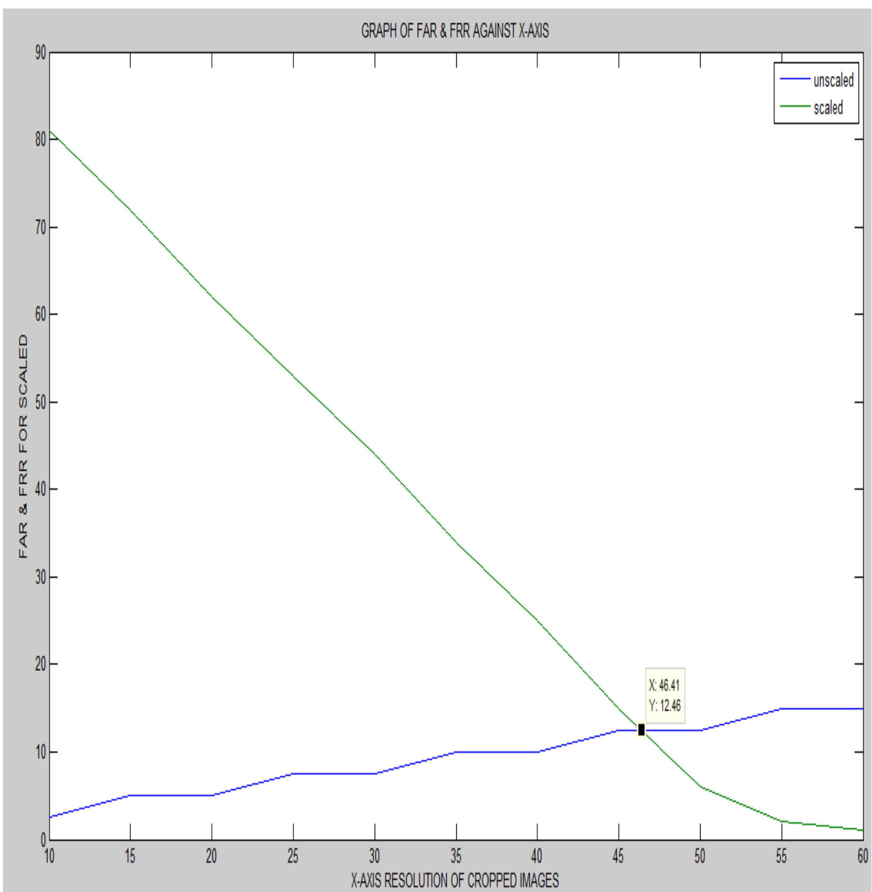

Fig. 6: False Acceptance Rate (FAR) and False Rejection Rate (FRR) for Scaled PCA-ANN

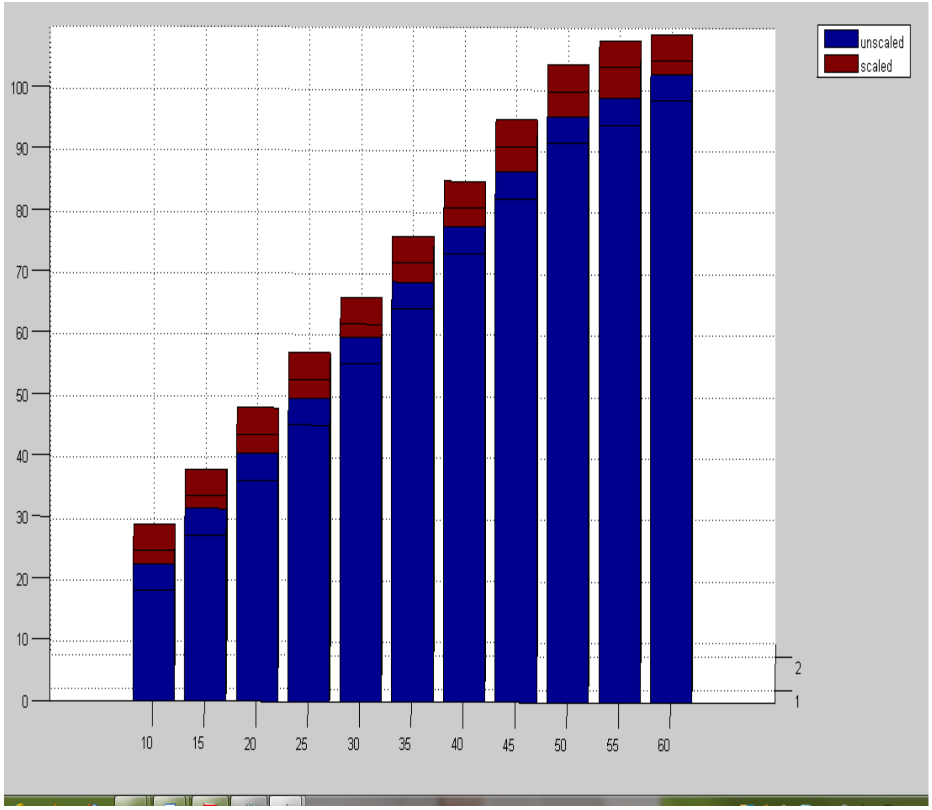

Fig. 7: Percentage Recognition for Different Resolution of Cropped Images

6. Conclusion

The palm vein recognition system using Hybrid Principal Component Analysis (PCA) and Self Organizing Map (SOM) has been developed. PCA was employed to reduce the dimension of the palm vein image. The SOM being a neural network was used to classify the vein patterns. The work resulted in overall success, being able to perform reliable recognition with image resolution of between 30*30 and 60*60. The application of the algorithms to the task of palm vein recognition requires a perfectly standardized and aligned database of palm vein. Palm vein cropping and image resizing were carried out before the dimensionality reduction stages to normalize the image before being subjected to algorithmic testing. Also, the training and testing images being matched together are of uniform sizes. Our approach produced promising result to be implemented in a practical biometric application.

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