Comparison Analysis between Implementation of Principal Components Analysis and Haar Wavelet as Feature Extractors in Palmprint Recognition System

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***Abstract*—One type of biometric system is human palmprint. The uniqueness and stability of the principle lines that makes characteristic of the palms reliable to be used as a means of recognition. The principle lines of palmprints are unique so that these can be used in recognition system. In this research, a recognition system using human palm based on Principal Component Analysis (PCA) and Haar wavelet transform for feature extraction. While for its identification, Euclidean distance was implemented. Both, individually, principal components and coefficient obtained from this extraction process then were implemented to determine minimum Euclidean distance. From the first test using PCA, when implementation of 150 training images of 40 respondents, it generated the lowest recognition rate. While, from the second test using Haar wavelet transform, it generated the highest recognition when the test using 7 training data. By these tests, it can be concluded that implementation of Haar wavelet transform gives better recognition rate rather than PCA. Two proposed methods produce good recognition rate but not the best when compared with other methods. The limited number of palms' specimens implemented is suspected of being the cause of its recognition rate is below other methods.**

Keywords—Palmprint recognition; feature extraction; identification; Principal Component Analysis (PCA); Haar wavelet transform; Euclidean distance

I. INTRODUCTION

The use of biometrics recognition systems have advantages over other systems such as the use of passwords, cards, keys, and others who have a deficiency when lost, forgotten, and more easily duplicated. Biometric systems are based on physiological human characteristic, behavioral, as well as chemical characteristics, e.g. face [1], fingerprints, voice, palmprint, iris, retina, DNA, or even odor [2]. The advantage of biometric systems is that it cannot be denied because something required to be accessing the user's direct presence in the process of recognition and have differences in each person so as to avoid duplication of cases of fraud or identity [3].

This reliability of the biometric system is the reason some developers needs to apply the business to meet human needs such as security systems, databases of population, health, and others both for identification and verification system [2]. Palm is one of biometrics which has unique characteristics such as principle lines palms are stable. It makes characteristic of the palms reliable to be used as a means of recognition [4]. The other reasons are that palmprints images are robust as palmprint features significantly do not change over time, as well as palmprint recognition system can perform well in extreme illumination and weather because it contain much more features set rather than other biometrics system [5]. Besides their advantages and effectiveness, there are disadvantages of Palmprint Biometrics, e.g. the palmprint scanners are usually bulkier and expensive since they need to capture a larger area than the fingerprints scanners [6]; and that there are some conditions which we cannot process some specimen of palm to the next processes because the palms are dirty, or there is an injury or some hurts which can change the pattern of normal palm. For this reason, the cleanliness and good conditions are the main requirements for specimen of palms to be recognized.

There are some algorithms which can be implemented to extract the features palmprint features. Some previous researches have been done related to palmprint principal lines feature extraction [7], fractal dimension method and lacunarity [8], and palmprint verification system [4]. Other research on palmprint also was done by Iskandar by doing a research on palmprint feature extraction using Haar wavelet and Euclidean Distance used as its similarity measure [9]. While Badrinath, et. al focused on palmprint recognition system using ID-DCT features [10]. Mistani, et. al proposed a hybrid feature which combines two sets of features, palm-line features and wavelet features [5]. Other research done by Daramola had concluded that palm image feature vector can be extracted using palm contour and image center of gravity. It has been tested using Euclidean distance measure and the result shows high interpersonal feature variation [11]. Ribaric and Marcetic proposed that palmprint feature can be extracted using Gabor filter, then its dimension is reduced using Principal Component Analysis (PCA), while Euclidean distance is used for 1-NN classification [12]. In other research, Imtiaz and Fattah demonstrated the proposed DCT-based local feature extraction algorithm for palmprint recognition where spatial domain local variation is extracted from frequency domain transform [13]. The previous researches explained that the feature extraction methods will impact the success rate of image identification. Based on the statement, this research will implement two of feature extraction methods and notify the better method to be used. The feature extraction methods used are a recognition system using human palm based on both Principal Component Analysis (PCA) and Haar wavelet transform. While for its identification, Euclidean distance similarity measure was implemented. The purpose of the research is a suggestion which the best combination of both feature extractor (i.e. PCA and Euclidean distance or Haar wavelet and Euclidean distance) when we implement Euclidean distance as a similarity measure in its identification.

II. Research Metodhology

A. Haar Wavelet Transform

In Haar wavelet transform, there are two processes, namely the forward transform and inverse transform. Forward transform is applied for decomposition, while inverse transform performs the reconstruction of the image.

In the advanced, wavelet transform carried decomposition image data, which begins with the filter in the horizontal direction (decomposition of the row) image data is then followed by a filter in the vertical direction (decomposition of the column) to the coefficient of the output image of the first stage or filter in the horizontal direction. The explanation on how the transform work can be depicted in Fig. 1.

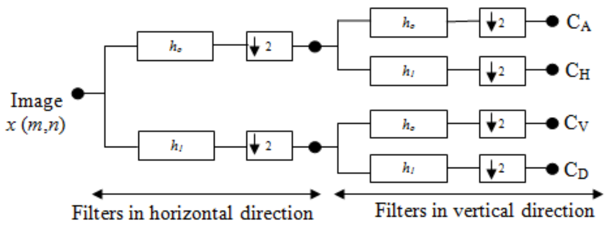

Fig. 1. Decomposition in Haar wavelet transform

Note:
h0 : low pass filter
h1 : high pass filter
CA: approximation coefficient or LL
CH: horizontal coefficient or LH
CV: vertical coefficient or HL
CD: diagonal coefficient or HH

Haar, together with other wavelet families, such as Daubechies, Coiflet, Symlet, and biorthogonal wavelets can be implemented in feature extraction, noise removing, and data compression. The area of the wavelets applications has been implemented. One example of application is the use of Haar, db4, and bior1.3 wavelets for application domain of wavelet transform in seismology and earthquake engineering which are increasing rapidly [14].

B. Principal Component Analysis(PCA)

Principal component analysis (PCA) is one of the most effective methods in both pattern recognitions as well as in data compression. The purpose of PCA method is used to remove data redundancy for both feature extraction and feature selection. Since PCA works in linear domain, it is also used in linear applications, such as, image processing, signal processing, communication, and system and control theory. PCA depends on eigenvector method which is designed to model linear variations in the data with large dimension [15]. The method used is transforming the original independent variables into new variables which are not correlated without removing significant information. These new variables then are called principal components. In order to reduce dimensionality, PCA is applied. Further, the sparse histogram is taken over the PCA output [16]. With this reduction, computation time can be diminished and the unnecessary complexity of palm images can be removed [17]. In PCA, there are some vectors called eigenvector and some values called eigenvalue which enable us to get most significant feature in the dataset [18].

A palm image with $N \times N$ sized and $I(x,y)$ indicate two-dimensional matrix *with* $N \times N$ sized which states the intensity values with size of 8 bits. Every pair of x and y indicates its position in the palm image. To be processed in the stages of both eigenvectors and eigenvalues processes, the matrix should be represented in a vector of N^2 sized which its elements from previous matrix and its row elements are rearranged consecutively.

To obtain eigenvalues and eigenvectors from an image database of palm, the first important thing to do is to determine the mean vectors, vector deviation and covariance matrix for the database. Stages that must be done to perform the calculations of eigenvalues as well as eigenvectors are as follows [7].

- The first step is to create a subset S consisting of palm images in the database.

$$S = \{ T_1, T_2, T_3, \ldots\ldots, T_M \} \tag{1}$$

  Each T_n is a vector (column) with dimension of N^2. The value of M is the number of palm images in database.

- The second step is to get the mean of vector with the formula:

$$\psi = \frac{1}{M}\sum_{n-1}^{M} T_n \tag{2}$$

- The third step is obtaining the difference (ϕ_n) between the images in the database (T_n) with its median (Ψ).

$$\Phi_n = T_n - \psi \tag{3}$$

- The fourth step is to calculate the value of covariance matrix (C) because mathematically principal component of the data is the Eigen vector of covariance matrix. Principal Component Analysis will look for a set of vectors that describe significantly a variety of data:

$$C = A.A^T \tag{4}$$

$$L = A^T.A \tag{5}$$

$$L = \Phi_m^T.\Phi_n \tag{6}$$

- The fifth step calculates Eigen value (λ) and Eigen vectors (v) of the covariance matrix (C).

$$C \times v_i = \lambda_i \times v_i \tag{7}$$

- The sixth step, after the eigenvector (v) is obtained, then eigen palm (μ) can be determined by:

$$\mu_i = \sum_{k=1}^{M} v_{ik} \Phi_k \tag{8}$$

Where l = 1, 2, 3, … M

Thus, the dimensions of the image can be reduced and then will speed up the calculation process. If the calculation process faster desired, it can be done by eliminating eigenpalm that only gives a small contribution [10].

C. Similiarity Measure using Euclidean Distance

After passing through feature extraction process and parameter values, in this case we obtain principal components. The next stage is calculating the nearest distance (Euclidean distance) of feature vector value of an image [8]. The closer the Euclidean distance, it is getting closer to a certain image. For example, values of feature vectors of reference image $A_i = (A_1, A_2, ..., A_n)$ and values of feature vector of tested image is $B_i = (B_1, B_2, ..., B_n)$, then Euclidean distance between values of feature vectors of reference image and values of feature vector of tested image can be expressed as:

$$D(A,B) = \sqrt{\sum_{i=0}^{n} \frac{(|A_i - B_i|)^2}{A_i}} \tag{9}$$

where:

$D(A,B)$ = Euclidean distance between image A and image B

A_i = Feature vector of image A

B_i = Feature vector of image B

n = vector length (sum of textural features) of vector A and vector B

Besides Euclidean as a similarity measure, there are some existing similarity or distance measures. There are 3 (three) classes of similarity, those are: Distance Class, Proximity Class, and Complex Class. For Distance Class, there exists: Euclidean Distance, Chebychev Distance, Hamming (City Block) Distance, and Minkowski Distance. Whereas, in Proximity Class, there are: Cosine Proximity, Correlation, and Jensen Proximity. In Complex Class, there are 3 (three) measures, i.e. Dynamic Time Warping (DTW), Optimized Regression Line (ORL), and Combinatorial Measure [19].

D. Feature Extraction and Recognition Processes

There are two main processes, i.e. feature extraction and recognition. The flowchart these two processes, including preprocessing can be shown in Fig. 3.

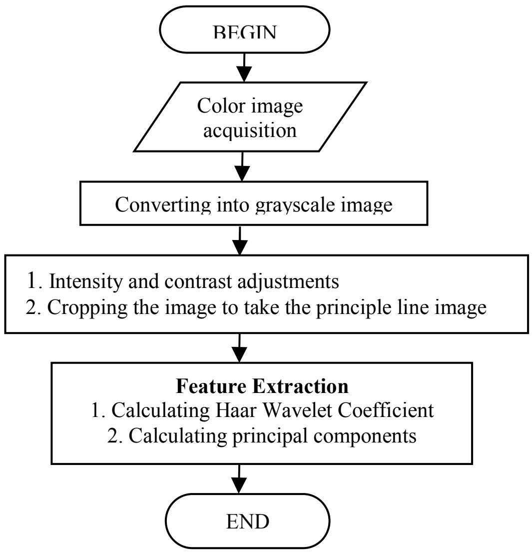

Fig. 2. Image preprocessing and feature extraction

Fig.2. depicts the preprocessing flowchart. In preprocessing, there are 3 (three) procedures, i.e. converting color image of palms into gray-level images, intensity or contrast adjustment, and image cropping to capture the palms' principle line images.

After the entire process of image preprocessing is completed, the image will go through the process of feature extraction. Feature extraction process carried out to obtain the essential features of the image of the palm. This feature extraction using Haar wavelet transform that serves to decompose the input image to get the approximation image (C_A), detail image for horizontal direction (C_h), detail image for vertical direction (C_v), and detail image for diagonal direction (C_d). In training process, it occurs a feature extraction process using Haar wavelet decomposition level 1 up to 4, while the feature extraction on the PCA obtains the values of principal components with variations of 50, 75, and 100. The flowchart these overall processes can be shown in Fig. 3.

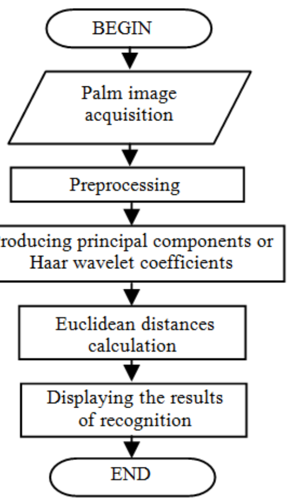

Fig. 3. Flowchart of overall process

The process of recognition is the identification stage of an image of palm that aims to identify whether the image of the palm matches to the user who is already registered in the database. This process is to make decision for an input image, whether it is “recognized” or “not recognized” by the system. The process begins with the identification of a specified acquired image of the palmprint to be recognized (test images). Having obtained the values of feature extraction results, then the next process is the recognition process using the similarity measure based on Euclidean distance. Decision identification is obtained by taking the smallest Euclidean distance. When the Euclidean distance does not exceed or equal to the threshold, the status of "recognized" and if it is less than the threshold then the status is "not recognized".

G. Simulation Setup

In developing the palmprint recognition system, some supporting tools are required. Some materials used can be differentiated into 2 (two) main categories, i.e., hardware and software. Some hardware used in this research are: Notebook set with the specifications: Processor Intel(R) core™ i5 with RAM 4 GB, and Microsoft Windows 7 OS; and the image acquisition hardware designed to recognize the palmprint consists of (a) a web-camera with resolution of 5 megapixels, (b) black board and (c) pegs. The distance of web-camera and black board is 36 cm with pegs conditioned so that the hand cannot change its position. Black board is 30 x 20 cm sized. Whereas the application software used is Matlab R2008a. In Matlab, there are many procedures as well as functions related to Image Processing, which are compiled in Image Processing Toolbox [20]. For wavelet programming, Wavelet Toolbox is available in Matlab [21].

The first step in this system development is data acquisition using hardware with many respondents invited. The number of responder invited is 40 persons. The number of palm images is 290 palms from 40 persons. From this number, 210 images from 30 persons are used as training images, 60 images from similar 30 person are used as test images and 20 images from 10 unregistered persons are used as untrained test images. In this experiments, some methods used in the research are explained, i.e. *first*, combination of Principal Component Analysis (PCA) and its similarity measure using Euclidean Distance; and *second*, combination of Haar Discrete Wavelet Transform and its similarity measure using Euclidean Distance.

III. Results and Discussion

In this section, there are two main discussions, i.e. testing results using Haar wavelet extractor and PCA extractor.

A. Haar Wavelet Extractor Implementation

Experiments were performed during the research using some variations on training data stored in the three database and decomposition level. Each of databases has different number of palm image as training data. Database 1 stored 1 palm image as the training data. The second database stored 3 palm images as the training data. The third database stored 7 palm images as the training data. The result has shown that the highest recognition which is 97,1% was obtained when using 7 training data 3 and the lowest, 41.8%, was obtained when using 1 training data. This results are depicted in Table 1 as well as in Fig. 4.

The highest recognition on decomposition level was 100% (not included test for outer images) in level 1 when using 7 training data; 98,4% in level 2 when using 3 training data and 61,7% in level 1 when using 1 training data. While the lowest recognition was obtained in level 4 when using 7 (database 3), 3 (database 2), and 1 (database 1) training data and has shown 95%, 75%, and 22%, respectively. The highest recognition in outer image resulted in 90% was obtained in level 1 using 7 training data. The best final result of recognition rate for combination both inside and outer image included in database is 97.5%

TABLE I. Percentage of Recognition Success Rate

Decompo-sition level	Database 1	Database 2	Database 3
1	61.7%	86.7%	100%
2	50%	93.7%	98,4%
3	33.4%	81.7%	95%
4	22%	75%	95%
Percentage average	41.8%	84.3%	97.1%

Furthermore, in tests using a threshold value above its Euclidean distance, in this research, threshold value is used to determine a limit value beyond the recognizable image or not. Without using a threshold value, an image which is outside of the test images will remain recognizable by the image stored in the database, because the identification process using the Euclidean distance takes the smallest distance or nearest similarity.

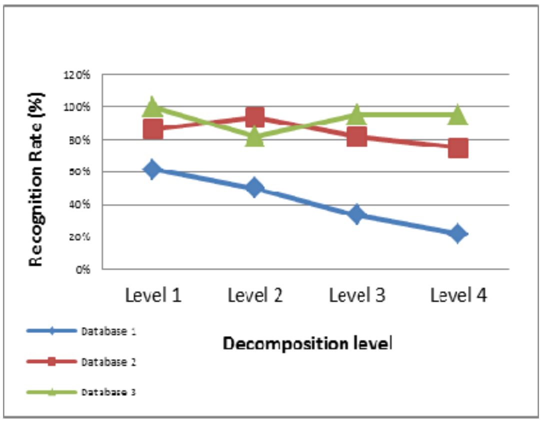

Fig. 4. Graphics of relationship between decomposition level and its recognition rate

In determining the threshold value in this research is by taking the largest value of a collection of the smallest Euclidean distance test results from test images against the training images [5]. Making the greatest value of the collection of the smallest Euclidean distance is intended to keep the recognition of test images that have trained and stored in the database. In the application of the identification of the palm is used variations in the number of training images and four levels of decomposition so that there are 12 threshold values for each level of decomposition on the variation of the number of images to train as shown in Table 2.

TABLE II. THRESHOLD VALUES FOR OUTER IMAGE TESTING

Database (number of training images)	Decomposition level			
	1	2	3	4
1 image	2392.37	2038.93	1856.34	1860.62
3 images	1747.29	1390.01	1244.09	1237.29
7 images	1353.18	1305.68	1198.27	1204.46

Test on the level of recognition in the data outside the database using a threshold value at each level of decomposition as shown in Table 3 which is graphically can be depicted in Fig. 5.

TABLE III. RESULT THRESHOLD VALUES FOR OUTER IMAGE TESTING

Decomposition level	Database 1 (1 training image)	Database 2 (3 training images)	Database 3 (7 training images)
1	0%	30%	90%
2	0%	25%	15%
3	0%	5%	0%
4	0%	0%	0%
Average rate	0%	15%	25%

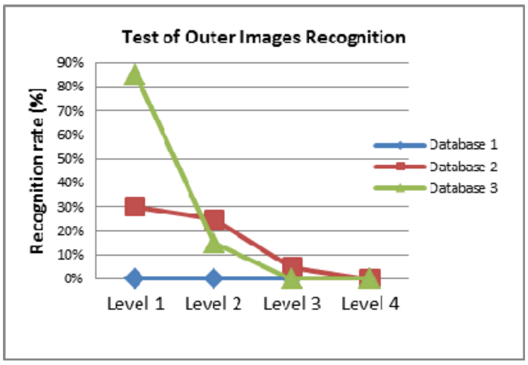

Fig. 5. Graphics of outer images recognition test

B. PCA Extractor Implementation

Experimental results show that there no significant relationship between a number of principal components implemented with its recognition rate (%). In this test, the recognition rates still remain in 90% rate. The test results can be depicted in Table 4 which are restated in graphics which is shown in Fig. 6.

In the next test to make the conditions more fair, we test 10 (ten) outer images which are not included in database. In this case, the threshold values are required. In determining the threshold value in this research, the sum of two statistical parameters are used, namely the maximum Euclidean value of all the test images coupled with 10 percent of the maximum value, the results of the previous test using test images. The threshold value obtained by the sum of the mean and standard deviation, its value is 0.006994 for 100 components, for 75 components of its value is 0.005814, to 50 components have a threshold value of 0.003686. This threshold value is then used to test images outside. The value is expected to be greater than the Euclidean distance on the image in the database. However, in this test, the number of principal components 100 is used. For the test using 10 outer images which are not included in database, all tests indicate "UNRECOGNIZED". Combining two tests with test images that are both included and not included in database, it produces the best recognition rate of 92.5%

C. Discussion

From the first test using combination of PCA and Euclidean Distance (ED), when we implemented 150 training images of 30 respondents and variations in the amount of 50,75, 100 principle components, it generated the same level of recognition, i.e. 90%. However, the experiments which involved 10 respondents from out of 30 both data of training and testing respondents which are not listed in the database had resulted that all respondents are not recognized, which matched with the purpose of this application.

While, from the second test using combination of Haar wavelet transform and Euclidean Distance, it can be concluded that the highest recognition, i.e. 97.1% was obtained when using 7 training data. The highest recognition on decomposition level was 100% in level 1 when using 7 training data; 98.4% in level 2 when using 3 training data and 61.7% in level 1 when using 1 training data. The highest recognition in outer image resulted in 90% was obtained in level 1 using 7 training data. By two tests with different combination of both feature extraction and identification, it can be concluded that implementation of Haar wavelet transform as feature extractor will give better recognition rate, i.e. 97.5% at average when 7 training data are used. While, when using PCA as feature extractor, it has the lower level of recognition, i.e. 92.5% at the average, in the amount of 50, 75, and 100 principal components.

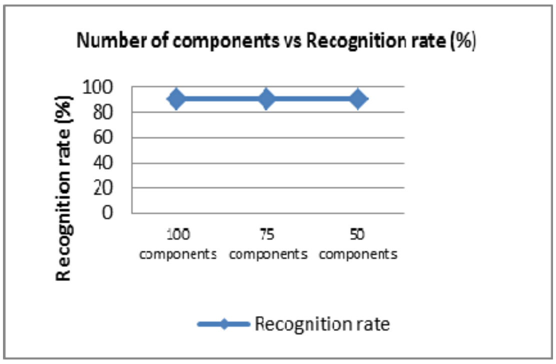

Fig. 6. Graphics for relationship between number of components and its recognition rate (%)

We have also provided a comparison of two proposed scheme with three earlier methods, i.e. multispectral palmprint recognition using a hybrid feature [5], based-on Gabor features on colour palmprint images [12], and DCT-based local feature extraction algorithm [13]. Table 4 depicts the comparison of these 5 (five) methods. As we can see, two proposed methods produce good recognition rate but those methods are not the best when compared with other methods. The limited number of specimen of palms which are implemented in this research is suspected of being the cause of the success rate to be "not satisfactory" comparing with other methods.

TABLE IV. COMPARISON WITH OTHER METHODS FOR PALMPRINT RECOGNITION

Methods	Recognition Rate
Haar + ED	97.50%
PCA + ED	92.50%
Hybrid feature [5]	98.88%
Gabor+PCA+ED [12]	98.71%
DCT+ED [13]	99.97%

In the future work, we will do research using more respondents or using large database of palms which are available online, e.g. from PolyU database [22]. The limited number of specimen of palms is suspected of being the cause of the success rate is not satisfactory comparing with other methods which are reported by other researchers. Regarding on the stability of recognition, it depends on the effect of increasing number of image data. Empirically, it can be inferred that the stability will be reached when the large number of both data training and testing image are applied. However, applying the large number of data is out of the recent research scope.

IV. CONCLUSION

From the tests and in-depth discussion, it can be concluded that: First from the first test using combination of PCA and Euclidean Distance, when we implemented 150 training images of 30 respondents and variations in the amount of principle components, it generated the same level of recognition, i.e. 90%; The experiments involved 10 respondents from out of 30 both data of training and testing respondents which are not listed in the database had resulted as not recognized 100%, which matched with the purpose of this application. Second, from the second test using combination of Haar wavelet transform and Euclidean Distance, it can be concluded that the highest recognition, i.e. 97.1% was obtained when using 7 training data. The highest recognition on decomposition level was 100% in level 1 when using 7 training data; 98.4% in level 2 when using 3 training data and 61.7% in level 1 when using 1 training data. The highest recognition in outer image resulted in 90% was obtained in level 1 using 7 training data. Three, by two tests with different combination of both feature extraction and identification, it can be concluded that implementation of Haar wavelet transform as feature extractor will give better recognition rate, i.e. 97.5% at average when 7 training data are used; When using PCA as feature extractor, it has the lower level of recognition, i.e. 92.5% at the average, in the amount of 50, 75, and 100 principal components.

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