Identity Recognition Based on Palm Vein Feature using Two-Dimensional Linear Discriminant Analysis

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***Abstract*—Research on biometrics continues to grow. Various studies conducted to increase the performance of personal identification based on physical and behavioral characteristics. Palm vein recognition became an interesting field lately. Palm vein feature covered underneath the skin so that it hard to forge and more resist to external factors than fingerprint and face features. In this research, recognition process consists of preprocessing, feature extraction and matching. Feature extraction has been done using Two-Dimensional Linear Discriminant Analysis. This method could reduce dimension by maximizing between-class scatter and minimizing within-class scatter. Two-Dimensional Linear Discriminant Analysis obtained a good performance for CASIA palm vein dataset. The configuration of parameters needs to be determined in order to increase the system performance. The best performance obtained 8% in term of EER and Recognition Rate 94,67% with threshold 0,4933.**

***Keywords*—biometrics; palm vein; two-dimensional linear discriminant analysis.**

I. Introduction

Identification system has been applied in various institutions such as banks, companies, and universities. Identification system which only uses a conventional method such as Personal Identification Number (PIN), password and Identity Card has low security. Biometrics system becomes an appropriate solution in order to decrease these problems. Biometrics is an automated recognition of individual based on their behavioral and physical characteristics such as fingerprint, face and palmprint. Biometrics is more effective than conventional method because it use the part of body characteristics [1].

One of biometrics trait that used lately is palm vein. Palm vein feature has more advantages compared to another biometrics; That can be build touchless, leave no trace on the device. difficult to duplicate because it covered underneath the skin and resistant to the change of temperature, weather and age. Moreover, everyone has different palm vein characteristics even if that person has a twin [2][3][4]. So that palm vein is a robust characteristics for identification system.

Feature extraction plays an important role in the palm vein recognition system. We can get the better performance by using the better feature extraction, but each biometrics trait may have different approach for extracting feature. Feature extraction which based on dimension reduction can reduce the dimension of data without losing important characteristics. Dimension reduction method that commonly used is Principal Component Analysis (PCA). PCA could extract the feature without losing important characteristics well [5]. Beside of that, Linear Discriminant Analysis (LDA) algorithm not only reducing dimension, it also maximizing between classes scatter and minimize within class scatter. So the features of LDA were more discriminating [6].

In this research, we used Two-Dimensional Linear Discriminant Analysis (2DLDA) as feature extraction method. This method is an improvement of LDA that could handle singularity problem of LDA. 2DLDA have been implemented successfully in [7] for face recognition, their research was comparing PCA+LDA and 2DLDA and obtained 2DLDA is more effective in performance and time than PCA+LDA for face recognition, Because of palm vein is more discriminating than face characteristic, we use 2DLDA for our palm vein recognition system with the hope of this system obtains a good performance.

II. Palm Vein Recognition System

Palm vein is a pattern of blood vessels that located underneath the skin of the palm. Palm vein has advantages as we discussed in the introduction. Palm vein image can be obtained by using a special device that use near-infrared (NIR) light.

Elnasir et. al. was made a review of feature extraction approach in palm vein recognition system as follows [6] :

a. Minutiae-based. This method using a feature which consists of starting and ending points of ridges, bifurcations, and ridge junctions among other features.

b. Texture based. This method using pattern of whole images, such as Gabor Filter, Local Binary Pattern (LBP), Local Derivative Pattern, etc.

c. Subspace projections. This method using feature after reducing image dimensions. This method trying to reduce dimensionality without losing the important feature of the image, such as Principal Component Analysis (PCA), Factor Analysis (FA), Linear Discriminant Analysis (LDA), etc.

Generally, our system consist of three steps, as shown in figure 1.

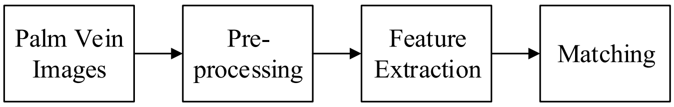

Fig 1. General System Block Diagram

In the preprocessing step, we applied the basic image processing technique (e.g. filtering, resizing, rotating), peak and valley detection and selecting the valley points using Competitive Hand-Valley Detection (CHVD) rules. We propose 2DLDA as a feature extraction technique and cosine similarity as a distance measurement.

A. Preprocessing

The purpose of preprocessing step is to get the ROI of palm vein images. Firstly, we did some basic image processing techniques that were rotation, binarization and median filtering to ease the peak and valley detection. To get the valley points, we detected the boundary of the hand and found the extreme points. After that, we selected the valley points of the hand by using Competitive Hand-Valley Detection (CHVD).

Competitive Hand-Valley Detection (CHVD) is the method we used for selecting points that were valley points of the hand. CHVD searches the location of each valley by checking extreme points. Valley points of the hand are [2]:

a. P1, valley point located between the thumb and the index finger.

b. P2, valley point located between the index finger and the middle finger.

c. P3, valley point located between the middle finger and the ring finger.

d. P4, valley point located between the ring finger and the little finger.

. In CHVD there are two observed points called checking point and current point. Checking points are points that located near current point and we used it to check if current point was in the hand region or not. In our system, we used two rules of CHVD for getting valley points [2]:

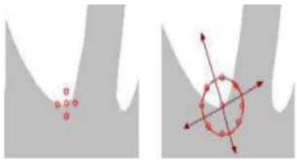

Fig 2. The first rule of CHVD

a. First condition was done by checking four points around current point with a distance of alpha (α). This rule selects the current point which only has one checking point that located in non-hand region.

b. Second condition was done by checking eight points around current point with a distance of alpha (α) + beta (β). In this rule, the current point at least has one and no more than four checking points that located in non-hand region selected as a valley.

After the second phase of CHVD, it gained four valley points depict in figure 3.

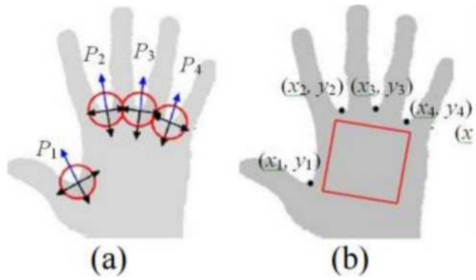

Fig 3. Valley Points and Cropping Area of ROI

After that we rotated the image so that P2 and P4 were in line. The last step of preprocessing was cropping ROI and saving it to the storage. The result of step-by-step image preprocessing can be seen in Figure 4.

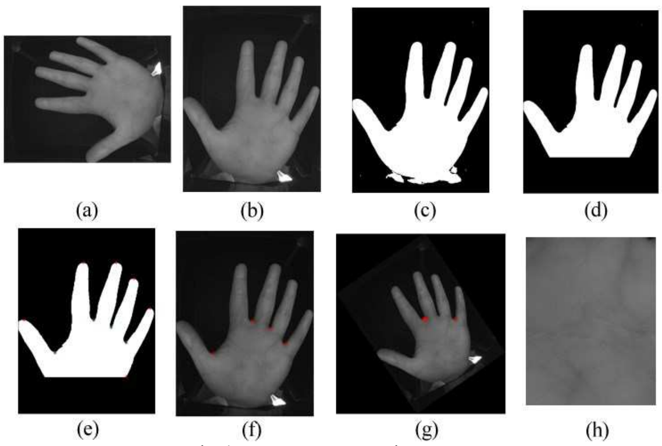

Fig 4. Image Preprocessing Steps

B. Feature Extraction using Two-Dimensional Linear Discriminant Analysis

Two-Dimensional Linear Discriminant Analysis (2DLDA) is the dimension reduction method and was an improvement method of Linear Discriminant Analysis (LDA) introduced by Fisher in 1936. 2DLDA projects the matrix into vector by maximizing between-class scatter and minimizing within-class scatter. This method has been proven to be efficient in class separation in [6] that applied in face recognition system. Unlike LDA, 2DLDA algorithm projects data into 2D matrix and this method obtained better performance than LDA[7]. 2DLDA projecting matrix defined as :

$$B = L^T AR \tag{1}$$

Where B is the feature, L is the column projection, R is the row projection, and A is the palm vein image. Firstly, we need to calculate class mean and global mean. Class mean (M_i) and global mean (M) using (2) and (3). where n is the number of image in a class and k is the number of class.

$$M_i = \frac{\sum_{j=1}^{n} A_j}{n} \tag{2}$$

$$M = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n} A_{ij}}{k \times n} \tag{3}$$

We need to find the row projection R and column projection L to get 2DLDA Features. Therefore we calculate the within-class scatter matrix and between-class scatter matrix of R which represented as S_W^R and S_B^R [7]:

$$S_W^R = \sum_{i=1}^{k}\sum_{j=1}^{n}(A_{ij} - M_i)RR^T(A_{ij} - M_i)^T \tag{4}$$

$$S_B^R = \sum_{i=1}^{k}(M_i - M)RR^T(M_i - M)^T \tag{5}$$

The optimal projection of R could be obtained by solving the following generalized eigenvalue [7]:

$$S_W^R x = \lambda S_B^R \tag{6}$$

After that, compute the within-class scatter matrix and between-class scatter matrix of L which represented as S_W^L and S_B^L by using equation 4 and 5.The optimal projection of L can be obtained by solving the following generalized eigenvalue using equation 6. Finally, projects A into 2DLDA feature using equation (1).

C. Matching and Performance Measurement

Given the set of labeled training and testing models. The first step of matching step is calculating a distance between training models and testing models using cosine similarity. Cosine similarity can be obtained using following equation :

$$d = \frac{A.B}{\|A\|\|B\|} \tag{7}$$

Where A and B are the training and the testing model, d is the cosine similarity between A and B. Then, we calculated confusion matrix based on d and *threshold*. The condition of confusion matrix can be seen in figure 5.

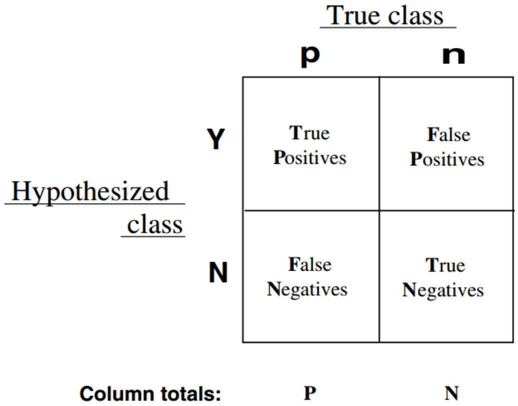

Fig 5. Confusion Matrix

There are four possible categories that can be observed from confusion matrix, that are True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN). If the sample is positive and classified as positive, it counted as TP. If the sample is positive and classified as negative, it counted as FP. If the sample is negative and classified as positive, it counted as FN. If the sample is negative and classified as negative, it counted as TN [8].

Performance measurement that we used in this research is Accuracy and Equal Error Rate (EER). Accuracy can be obtained using following equations [8]:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{9}$$

EER is one of the performance measurement that usually used for identification system. EER can be measured by getting the intersection of False Acceptance Rate (FAR) and False Rejection Rate (FRR) depict in figure 6.

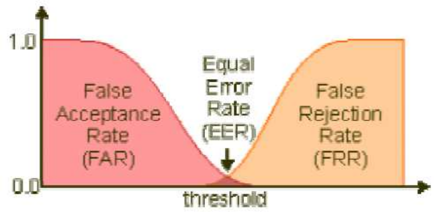

Fig 6. The illustration of Equal Error Rate

FAR measures the percentage of the system accepts a wrong class. FAR happens when there is an impostor that accept as genuine class. FRR happens when there is a genuine class that rejected by system. FAR and FRR can be measured by the following equation.

$$FAR = \frac{FP}{FP + TN} \tag{10}$$

$$FRR = \frac{FN}{TP + FN} \tag{11}$$

III. EXPERIMENTAL PREPARATION

A. *Dataset*

In this research we used CASIA Multi-Spectral Palmprint Database with the length of infrared 850 nm and the left-hand images. Dataset consist of 600 palm vein image collected from 100 persons. Each person have six palm vein images which taken in two sessions. Images with id 1,2 and 3 were taken at the first session while id 4,5,6 were taken at the second session and were darker than the first. Dataset is divided into training and testing with ratio 3:3.

B. *Experiment Scenario*

These are four scenarios of testing step in this system :

a. The first experiment is to analyze the effect of quality of image acquisition. Data training/testing that used are 1,2,3/4,5,6; 1,2,4/3,5,6; 1,4,5/2,3,6; and 4,5,6/1,2,3. The constant parameters are ROI dimension is 100x100, 2DLDA dimension is 4x4, and Threshold is 0,5.

b. The second experiment objective is to analyze the effect of ROI dimension. We used dimension 50x50, 100x100, 150x150, 200x200 and 250x250. The constant parameter is the best configuration of first scenario.

c. The third experiment is to analyze the effect of 2DLDA dimension. We used dimension 4x4, 8x8, 12x12, 16x16 and 20x20. The constant parameter is the best configuration of second scenario.

d. The fourth experiment is to measures performance based on error rates. We used threshold value from 0 to 1 and the constant parameter is the best configuration of third scenario.

IV. EXPERIMENTAL RESULT

A. *Experiment 1*

The result of the first scenario depict in figure 7.

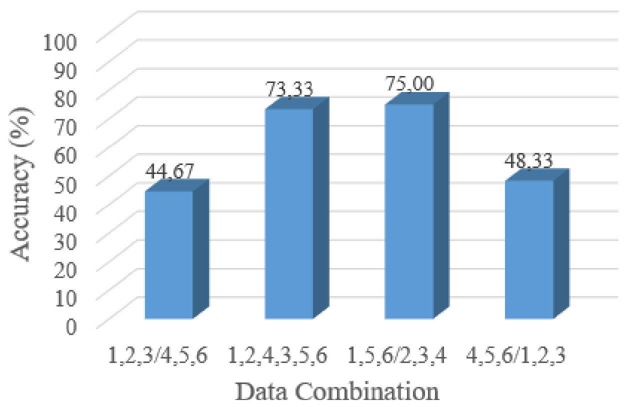

Fig 7. The result of the first scenario

In this scenario, the highest accuracy obtained was 75%. Figure 7 shows that lighting levels of the images affects the system performance. Based on the first experiment, in order to get a better performance, the training image should contain images of first and second session. The training that consist of only bright or dark image obtained worse accurate than training data that consist of bright and dark images. Based on this experiment, we use training set 1,5,6 and testing set 2,3,4 on Experiment 2.

B. *Experiment 2*

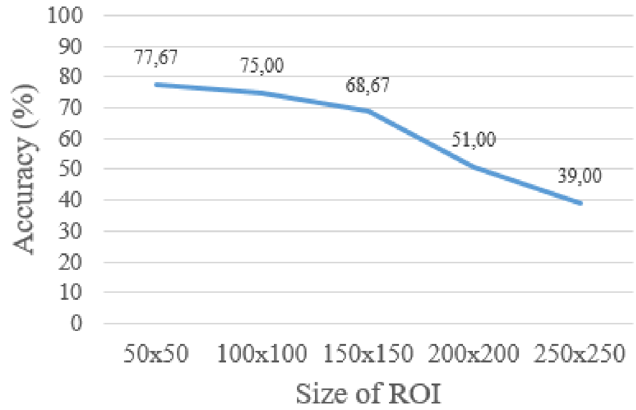

Fig 8 The result of the second scenario

As shown in figure 8, changing of the size of ROI will produce a trend that the larger ROI dimension, the smaller accuracy. Based on this experiment, we use ROI dimension with size 50x50 in the Experiment 3.

C. *Experiment 3*

The result of the third scenario can be seen in Fig.9.

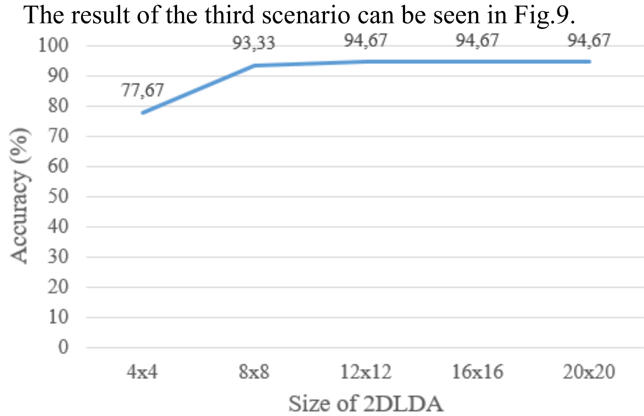

Fig 9. The result of the third scenario

The best performance obtained 94,67% of accuracy. From figure 9 we can see that the parameter of 2DLDA dimension 12x12, 16x16 and 20x20 obtained the same accuracy. Therefore, we use 12x12 2DLDA dimension in Experiment 4 because it was faster in computation than the others.

D. Experiment 4

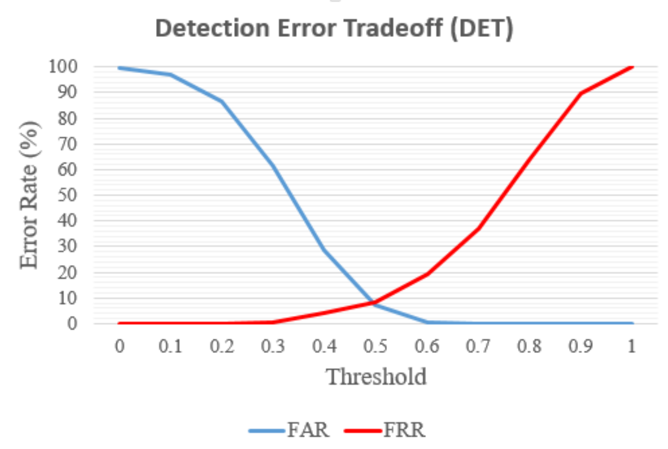

Fig 10. The result of fourth experiment

The best performance obtained 8% of EER with threshold 0,4933. We use that threshold to measures the rates of the system using training/testing 1,5,6/2,3,4, 50x50 ROI dimension, 12x12 2DLDA dimension. This experiment obtained accuracy 94,67%.

V. Conclusion

The best accuracy obtained when training and testing data consist of bright and dark image. Dimension of ROI and 2DLDA can affects system performance therefore needs to be determined the best configuration of ROI dimension and 2DLDA dimension. This system cannot handle illumination of the image so the training set should consist of image from two sessions to get the best performance. The best configuration is 1,5,6 training set, 2,3,4 testing set, 50x50 ROI dimension, 12x12 2DLDA dimension and 0,4933 threshold. The optimal performance obtained EER 8% and accuracy 94,67%, so that Two-Dimensional Linear Discriminant Analysis is good to be implemented in palm vein recognition system with CASIA dataset, but this training system should consist of two session may obtains better or worse performance with another dataset because of the different characteristics of datasets. Therefore, the further studies are needed.

VI. Future Works

In the future, further experiments are needed to be conducted to increase the performance such as using other preprocessing technique, using another dataset, or combining 2DLDA with other methods to get better performance.

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