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Multilayer Perceptron Neural Network in Classifying Gender using Fingerprint Global Level Features

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Abstract

Background/Objective: A new algorithms of gender classification from fingerprint is proposed based on Acree 25mm2 square area. The classification is achieved by extracting the global features from fingerprint images which is Ridge Density, Ridge Thickness to Valley Thickness Ratio (RTVTR) and White Lines Count. The objective of this study to test the effectiveness of the this new algorithm by looking the classification rate. Multilayer Perceptron Neural Network (MLPNN) used as a classifier. **Methods:** This new algorithm is tested with a database of 3000 fingerprint in which 1430 were male fingerprint and 1570 were female fingerprints. Classification part is tested with different test option. **Findings:** This study found that women tends to have higher Ridge Density, higher white lines count and higher ridge thickness to valley thickness ratio compared to male same as the previous study. Therefore, we can conclude that this new algorithm is very efficient and effective in classifying gender. **Conclusion:** The overall classification rate is 97.25% has been achieved.

Keywords: Fingerprint, Gender Classification, Global Features, Multilayer Perceptron Neural Network

1. Introduction

Gender information is important to provide investigative leads for finding unknown person. Existing methods for gender classification have limited use for crime scene investigation because they depend on the availability of teeth, bones or other identifiable body parts having physical features that allow gender determination by conventional methods[1].

Several studies have investigated the use of other biometric modalities to determine gender, including the face[2], gait[3], iris[4], hand shape[5], fingertip[6] and finger length[7]. For this research, gender of a person is identified from the fingerprint because of the fingerprint is one of way in gender classification or recognition that used to minimize the criminals suspect list in forensic anthropology[8]. Fingerprint analysis plays a role in convicting the person responsible for an audacious crime. Generally, fingerprints used for identification or verification of a person and for official documentation[7].

Nowadays, fingerprint has been used as a biometric[19,21] for the gender classification because of its unique nature and do not change throughout the life of an individual[9]. This is due to their high acceptability, immutability and uniqueness of the fingerprint itself. The immutability of the fingerprint refers to the pattern that remains unchanged over time, whereas uniqueness related to the differences of individual ridge details across the whole fingerprint image[10].

Fingerprint is a pattern on the fingertip and consists of ridges and valleys. The ridges are the black lines and the latter are white area between two adjacent ridges. This is shown in Figure 1 below.

The fingerprint basically has two properties named as individuality and persistence. It is individuality as the fact that the fingerprint is unique across individual and across fingers of the same individual. The persistence property makes sure that the basic fingerprint characteristics do not change over time. There are two levels of features in fingerprint structure: global and local. The global level is associated with the patterns of ridges and valleys on the fingerprint whereas the local level is corresponding to the minutiae.

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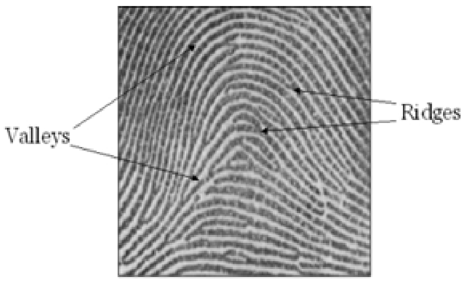


Figure 1. The ridge and valley.

2. Methodology

The sample of this study consists of 300 respondents from Malaysian people, which are 143 males and 157 females. All the respondents had been properly explained about the objectives of the intended study and the consent had been taken before their fingerprints collected. All 10 fingerprint images that are taken manually are going through be scanned before. Image preprocessing is focuses in removing the unimportant information of the fingerprint images[20]. In this study, image being pre-processed using normalization and binarization[20] to reduce any noise[18] and intensity of a latent fingerprint image. The sample result shown in Figure 2(a), Figure 2(b) and Figure 2(c).

In this paper, we will use the global level features in the fingerprint which is the ridges to determine the ridge density, RTVTR and white line count. An implementation of new algorithms in calculating the features which are Acree 25 mm^2 square area method[11] are implemented in the upper portion of the radial and ulnar border in the fingerprint image calculated using Formula (1).

The location of square area (25 mm^2) on the fingerprint image is determined to be on the upper side of the centre core region. The location of the square area in the central core region is avoided as it has the variability of pattern shapes and recurving ridges. The process of calculating ridge density shown as below:

2.1 Step of Ridge Density Calculation

- Read an image from the database.
- Show image to the screen.
- Assign 25 mm^2 box area to an ulnar/radial position.
- Crop the image.
- Show the image after cropped.
- Resize image for 256 x 256 pixels.
- Do a normalization pre-processing.
- Compute a background of an image.
- Do a binarization pre-processing.
- Show the binary image.
- Identify the image and compute the number of white lines (ridges).
- Compute the ridge density using Formula (1).

The white line count is calculated manually,while the ridge thickness to valley thickness ration calculated by using the Formula in (2).

Number of white pixels represent the no. of ridges pixel and number of black pixels represent a number of valley pixel in the 25 mm^2 square area fingerprint image. The process of calculating RTVTR shown as below:

2.2 Step of RTVTR Calculation

- Read an image from the database.
- Do an image preprocessing (normalization and binarization).
- Show image to the screen.
- Assign 25 mm^2 box area to an ulnar/radial position.
- Crop the image.
- Show the image after cropped.
- Resize image for 256 x 256 pixels.
- Set the loop to 256 x 256 pixels.
- Calculate the total white pixel and black pixel.
- Calculate the RTVTR using Formula (2).
- Show the answer.

3. Results and Discussion

3.1 Ridge Density

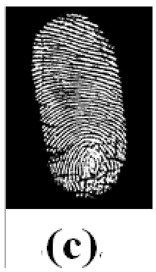
Table 1 shows that the mean number of ridge count for all 10 fingerprints for each participant and percentages of mean ridges count for every class of mean. The result shows that the male respondent tends to have lower mean number of ridges with the maximum number of it in the range of group H which is 16.1-16.9 compared to female respondent with a maximum mean no. of ridge in group J which is 18.1-18.9.

(a)

Figure 2. Original latent fingerprint images.

(b)

Figure 2. Fingerprint images after normalization.



(c)

Figure 2. Fingerprint images after binarization.

Figure 3. Square area (25 mm2) for ridges density,

In terms of percentage, 41% of female respondent majority in group H with the range mean no. of ridge 16.1-16.9 while male respondent 35% majority in group C with the range of 11.1-11.9.

Table 2 shows the descriptive statistical of ridge count for both male and female respondent. It is shown that the mean for male and female respondent for Malaysian population is around 11.8231 and 16.3494 each with the standard deviation of 1.3793 and 1.1143. The standard error for each gender is 0.1153 for male respondent and 0.8922 for female respondent.

3.2 White Lines Count

Table 4 shows that the number of white lines counts for each participant. The result shows that the male respondent tends to have a lower number of white lines with the maximum number of 14 compared to female respondent with a maximum number of white lines with the maximum number of 21. Majority female respondents have the 17 white lines count while majority male respondents have 10 white lines count.

Table 5 shows the descriptive statistical of white lines count for both male and female respondent. It is shown that the mean for male and female respondent for Malaysian population is around 11.9 and 17.38 each with the standard deviation of 1.462 and 2.256. The standard error for each gender is 0.124 for male respondent and 0.181 for female respondent.

Table 1. No. of ridge count against male and female respondent

Class	Mean Number of Ridge	No of male respondent	No of female respondent
A	9.1-9.9	3	0
B	10.1-10.9	37	0
C	11.1-11.9	50	0
D	12.1-12.9	31	0
E	13.1-13.9	13	2
F	14.1-14.9	2	12
G	15.1-15.9	4	39
H	16.1-16.9	3	65
I	17.1-17.9	0	24
J	18.1-18.9	0	15
	Total:	**143**	**157**

3.3 Ridge Thickness to Valley Thickness Ratio (RTVTR)

Table 7 shows that the range number of ridge thickness to valley thickness ratio for each participant. The result shows that the male respondent tends to have lower mean values of ridge thickness to valley thickness ratio with the maximum amount of it in the range of group 5 which is 0.71-0.79 compared to female respondent with a maximum ridge thickness to valley thickness ratio in Group 11 which is 1.31-1.39. The majority of female respondent in Group 3 with the range ridge thickness to valley thickness ratio is 0.51-0.59 while majority male respondent in group 6 with the range of 0.81-0.89.

Table 8 shows the descriptive statistical of ridge thickness to valley thickness ratio for both male and female respondent. It is shown that the mean for male and female respondent for Malaysian population is around 0.53708 and 0.8113 each with the standard deviation of 0.08894 and 0.1847. The standard error for each gender is 0.00752 for male respondent and 0.01479 for female respondent.

Table 2. Descriptive statistics of ridge density for both male and female

	Male	Female
Minimum	9.5	13.6
Maximum	16.9	18.9
Median	11.6	16.2
Mean	11.8231	16.3494
Standard Deviation	1.3793	1.1143
Standard Error	0.1153	0.8922

Table 4. No. of white lines count against male and female respondent

Number of White Lines (WLC)	No of Male respondent	No of Female respondent
9	13	0
10	42	0
11	33	0
12	28	1
13	18	4
14	8	8
15	0	15
16	0	24
17	1	42
18	0	25
19	0	17
20	0	10
21	0	6
22	0	0
23	0	5
Total:	143	157

Table 5. Descriptive statistics of white lines count for both male and female

	Male	Female
Minimum	9	12
Maximum	17	23
Median	11	17
Mean	11.9	17.38
Standard Deviation	1.462	2.256
Standard Error	0.124	0.181

3.4 Classification Rate

The result of gender classification is given in Table 10. The result shows that Multilayer Perceptron Neural Network (MLPNN) gave 95% accuracy and above for classification rate, which is the highest is 100% accurate, using 80% train 20% test, but this cannot be accepted as the best accuracy due to the small number of testing data. As the 10 fold cross validation taking all data sets to be trained and tested, we can assume that accuracy given by 10 fold cross validation is the best accuracy to measure the effectiveness of our algorithms.

The process of 10 fold cross validation find the mean accuracy of the data trained and tested. This process breaks data into 10 sets of size dataset and train on 9 datasets and test on 1 datasets. The process repeated 10 times and takes the means accuracy of the classification.

As we can see the confusion matrix for 10 fold cross validation in Table 9, a represent male dataset and b represent female datasets. There is just a small number of datasets predicted negative that are actually positive for male and female compared to the datasets that are predicted to be positive that are actually positive.

This result is compared with the earliest published result of gender classification using different methods of feature extraction. The result of Badawi et al.[12] is compared with RTVTR, ridge count, white lines count using NN classifiers. Overall classification rate achieved is 87.64%. The result of Manish et al.[13] is compared on RTVTR and ridge density using SVM as a classifier. Overall classification rate achieved is 88%. Gnanasivam et al.[14] studied using KNN as a classifier to see the performance of their new proposed method. Overall classification rate achieved is 88.28%. Gupta et al.[15] combining two methods for gender classification which is Discrete Wavelet Transform (DWT) as a feature extraction method and Back Propagation Artificial Neural Network (ANN) algorithms as a classification technique that used for the process of gender identification. An overall classification rate is 91.45% has been achieved. Rajesh et al.[16] proposed Discrete Wavelet Transform (DWT) for analyzing the fingerprints in the frequency domain and Gaussian Mixture Model (GMM) for classifying the dominant features by rank. GMM have been chosen because of the ability to approximate the distribution of the patterns representing the characteristic of a texture in an image. They achieved 92.67% at 3rd level DWT decomposition. Ceyhan et al.[17] investigates if there is a relationship between fingerprint and gender or not. In their studies, the relationship is examined based on some vectorial parts of fingerprints.They state that the dermal ridge density of a certain area of a fingerprint shows the variance according to gender and ethnic background. The experiment has been done using 4 different type classifier which is Naive Bayes (NB), k Nearest Neighbor (KNN), Decision Tree and Support Vector Machine (SVM) They achieved 95.3% of the success of the gender classification by using Naive Bayes classifiers.

Gender classification accuracies of the proposed method and the published results shown in Table 10.

Table 7. No. of RTVTR against male and female respondent

Class	Ridge Thickness to Valley Thickness Ration (RTVTR)	No of Male Participant	No of Female Participant
1	0.31-0.39	4	0
2	0.41-0.49	41	1
3	0.51-0.59	63	16
4	0.61-0.69	33	29
5	0.71-0.79	2	29
6	0.81-0.89	0	37
7	0.91-0.99	0	24
8	1.01-1.09	0	7
9	1.11-1.19	0	5
10	1.21-1.29	0	4
11	1.31-1.39	0	4

Table 8. Descriptive statistics of RTVTR for both male and female

	Male	Female
Minimum	0.3275	0.4575
Maximum	0.7777	1.3809
Median	0.5452	0.8122
Mean	0.53708	0.8113
Standard Deviation	0.08894	0.1847
Standard Error	0.00752	0.01479

Table 9. Result of Multilayer Perceptron Neural Network for different test option

Test Option	Accuracy (%)	Time Taken	Confusion Matrix
60% Train 40% Test	95.7627	22.19 seconds	a b 48 4 | a 1 65 | b
70% Train 30% Test	97.7528	22.4 seconds	a b 37 1 | a 1 50 | b
80% Train 20% Test	100%	22.6 seconds	a b 31 0 | a 0 28 | b
10 Fold Cross Validation	97.6351	21.93 seconds	a b 137 3 | a 4 152| b

From the result, we found that women tend to have a higher ridge count, white line count and Ridge Thickness to Valley Thickness Ratio (RTVTR) as been write by[11]. It can strengthen the[11] hypothesis which are women tends to have a higher ridge density compared to a woman.

Besides that, this algorithm is to improve gender classification problem for making the process of classifying more ease than before. Before this, there are so many researchers from forensic world still using manual ways of calculating the ridge. The process of identifying the pattern is very complex and takes time as it is done manually. From this study also, we found that Multilayer Perceptron Neural Network gives better accuracy for this result compared to others.

4. Conclusion

In this work, we have proposed a new algorithm based on Acree 25 mm^2 square area for gender classification of a latent fingerprint image. By the proposed method, the overall gender classification rate achieved 97.25% using the Multilayer Perceptron Neural Network as a classifier.

Our future work is to test this new algorithm with others classifier because we aimed to increase the success rate and find the suitable classifier for this proposed algorithm. We also want to compare on our algorithm using the same dataset with the other gender classification algorithm in order to see the effectiveness and efficiency of the proposed algorithms.

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Table 10. Comparison of fingerprint gender classification accuracies

Authors	Classifier	Accuracy
Badawi et al.[12]	Neural Network (NN)	87.64%
Manish et al.[13]	Support Vector Machine (SVM)	88%
Gnanasivamet al.[14]	k- Nearest Neighbors (KNN)	88.28%
Gupta et al.[15]	Back Propagation Artificial Neural Network (ANN)	91.45%
Rajesh et al.[16]	Gaussian Mixture Model (GMM)	92.67%
Ceyhan et al.[17]	Naive Bayes (NB)	95.3%

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