FINGERPRINT CLASSIFICATION USING SUPPORT VECTOR MACHINE

BY

HO KAH WENG

A REPORT

SUBMITTED TO

Universiti Tunku Abdul Rahman

in partial fulfillment of the requirements

for the degree of

BACHELOR OF COMPUTER SCIENCE (HONS)

Faculty of Information and Communication Technology

(Perak Campus)

June 2020

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DECLARATION OF ORIGINALITY

I declare that this report entitled "<u>Fingerprint Classification Using Support Vector</u> <u>Machine</u>" is my own work except as cited in the references. The report has not been accepted for any degree and is not being submitted concurrently in candidature for any degree or other award.

Kohmeny

Signature

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Name	:	HO KAH WENG

Date : <u>02/09/2020</u>

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ABSTRACT

Biometrics is metrics of human characteristics. The identification or verification of an individual can be done through biometrics authentication by extracting the human characteristic data. One of the most well-known and most used methods for identification is fingerprint recognition. Fingerprint recognition is the automated process of identifying the identity of an individual based on the comparison of two fingerprints. Fingerprints are completely unique to every human. Each individual's finger has different tiny ridges, valleys and patterns. In order to reduce the search time of fingerprints in a database, classification is needed. However, the quality of the fingerprint images may vary depending on the hardware that is used to capture the images. Noise may occur when capturing a fingerprint images. In order to classify the fingerprint into different categories accurately, a noise reduction steps has to be done. In this project, a fingerprint classification method using Support Vector Machine that includes a noise reduction method is developed. The accuracy of the classifier is also compared with others that use different noise reduction method.

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LIST OF ABBREVIATIONS

- RL Right-Loop
- W Whorl
- A Arch
- SVM Support Vector Machine
- DWM Directional-Weighted-Median
- RBF Radial Basis Function

CHAPTER 1: PROJECT BACKGROUND

1.1 Background Information

Biometrics is a form of body calculations and measurements. It is also refers to metrics of human characteristics. The identification or verification of an individual can be done through biometrics authentication by extracting the human characteristic data. Implementation of biometrics in authentication technology has become very popular these days as the possibility of hacking increases with the development of technology.

One of the most well-known and most used methods for identification is fingerprint recognition. Fingerprint recognition is the automated process of determining, identifying or confirming the identity of an individual based on the comparison of two fingerprints. Fingerprints are completely unique to every human. Each individual's finger has different tiny ridges, valleys and patterns on every finger as shown in Figure 1.1 below. This makes fingerprint recognition a good authentication method.



Figure 1.1 Fingerprint ridges and valleys

Optical readers are the most common fingerprint reader hardware used in a fingerprint recognition process. The type of sensor in optical readers is a digital camera that captures a visual image of human's fingerprint. Besides, there is another type of fingerprint reader hardware, which is the capacitive reader. Capacitive readers do not read fingerprint using light. Instead they use capacitors and electrical current to construct an image of the fingerprint. There is also a type of hardware that uses high

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frequency sound waves, which is the ultrasound readers. The last type of fingerprint reader is thermal readers. They determine the difference of temperature in between fingerprint ridges and valleys.

Fingerprint classification is a process where fingerprints are grouped into different categories such that fingerprints in the same category will have the similar pattern and is different to the patterns of fingerprint in other categories. There are several different types of fingerprints, which are Left-loop (LL), Right-loop (RL), Whorl (W) and Arch (A). The figure below shows the different categories of fingerprints.



Figure 1.2 Different categories of fingerprints

1.2 Problem Statement

Fingerprint recognition is a good identification methods used in these days. However, the recognition of fingerprint is very dependent on the quality of fingerprint images that is being scanned and captured using the hardware. Problem happens when fingerprint images captured is not clear, some images of the fingerprints have broken ridges and some images can be blurry. It is difficult to classify the fingerprints when the images are affected by the noise.

1. Ridges in fingerprints break and discontinue due to noise

Noise is the cause of errors during the process of acquiring image that result in values of pixel that do not match the true intensity of the real scene. Some of the fingerprint images may contain noise caused by some factors. These factors include dirt grease, moisture, damaged outer skin of the fingerprint and even bad quality of input devices. Therefore in some noisy fingerprint images, ridges may not be very clear; hence causing the fingerprint images cannot be correctly detected. Due to the presence of noise in the image, it may greatly decrease the recognition performance of the system. Noise will also cause singular points on fingerprint to be missing in a fingerprint image. Singular point also known as singularity is landmark on a fingerprint. It consists of core and delta, which are mainly used when classifying fingerprints and also as alignment in automatic fingerprint identification systems. Figure 1.3 below shows the singular point in a fingerprint image.



Figure 1.3 Singular points in a fingerprint

2. Classification of fingerprints may be inaccurate due to blur fingerprint images

Noise is the main factor that caused errors when classifying fingerprints. Noise caused by various factors can lead to unclear ridges as well as missing singular points in fingerprint images. Singular points are usually very important when it comes to classifying fingerprints since they are often used in fingerprint classification. The number of cores and deltas will help to determine the category of the fingerprint. Most of the time, the noisy fingerprint images will be blurry. This will toughen the process of identifying the number of deltas and cores in a fingerprint, therefore causing the process of fingerprint classification to be difficult and sometimes leads to classifying the fingerprint into a wrong category. Figure 1.4 below shows an example of blurred fingerprint image.



Blurred Image

Figure 1.4 Blurred image of fingerprint

1.3 Project Scope

The focus of the project is to develop a fingerprint classification method that implements a noise reduction function that helps to reduce the noise when a fingerprint image is being scanned and captured. The main image resource is a dataset of fingerprint images obtained from online that is scanned using an optical reader. These images include clear and blurry images to test the performance of the proposed method. In this project, the following methods are implemented.

1. Noise Reduction

Image noise means random variation or colour information in an image. In a simpler term, it refers to visual distortion. There are several types of different noises. The most common noise is known as the Gaussian noise and also the Salt-and-pepper noise.



Figure 1.5 Fingerprint image with Salt-and-Pepper noise (Subba, 2014)



Figure 1.6 Fingerprint image with Gaussian noise (Subba, 2014)

The other types of noise include shot noise, quantization noise (uniform noise), film grain, anisotropic noise, and periodic noise. Noise reduction is the procedure to reduce and remove noise from an image. The noise reduction function implemented in the proposed method is to reduce the noise in a fingerprint image that caused by various factors. After the noise in the images have been reduced and removed, a fingerprint image with better quality is produced to ease the process of fingerprint classification.

2. Classification using Support Vector Machine

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Classification of fingerprint is considered as a coarse level matching of fingerprints. The input of fingerprint is first matched to one of the pre-specified categories. Then it is compared to a database subset that is corresponding to the fingerprint type. A classification algorithm is divided into two main parts, the feature extraction and the classification scheme. The fingerprint classification method that implemented is the Support Vector Machine (SVM). The aim of implementing this technique into this project is to increase the performance and effectiveness of the classification method. It is to help others by classifying large quantity of fingerprints into different categories or classes accurately to reduce the search time.

1.4 Project Objectives

The main objective of this project is to develop a fingerprint classification method. This project is to develop a classification method that is able to reduce the noise of a fingerprint image and enhance the quality of the image for a better classification process.

1. To reduce the noise of a fingerprint image

A fingerprint image is very important when it comes to fingerprint recognition. If noise is present in a fingerprint image, it will affect the recognition process and even the authentication of the identity of an individual. There are also some blurry fingerprint images, causing the singular points to be missing and difficult to identify. In order to improve the recognition process, it is better to reduce as much noise as possible on a fingerprint image.

2. To classify the fingerprint image

Classification of fingerprint is necessary to speed up the database search in a fingerprint identification system. With the classification of fingerprints, a huge database of fingerprints can be partitioned into different classes or categories to increase the performance of retrieving the correct fingerprint in the system. Therefore, it is very important to improve the performance of fingerprint classification.

1.5 Project Contribution, Impact and Significant

This project is able to contribute to users by increasing the performance at work. With the noise reduction and enhancement method implemented into the fingerprint identification system, it will help users classify and store the different fingerprints into different categories much easier. The classification of fingerprints is very important in the industry especially in fingerprint identification system. This is due to the fact the many fingerprints are being collected and stored into the system every day. Fingerprint classification reduces the search space of a large database. With the fingerprints in the system classified, it will be easier and require much less time to retrieve the specific fingerprint that is needed. The system will only need to determine the types of fingerprint of the user and just search through fingerprints in that particular category, instead of searching for the fingerprint in a database with millions of different fingerprints.

1.6 Chapter Summary

Fingerprint recognition is a very popular individual identification method. Each individual has unique ridges and valleys on their fingerprints. The most common type of fingerprint reader hardware is the optical fingerprint reader. However, there exists some problems with the fingerprint images that is retrieved using optical readers, which is the noise caused by some factors. Fingerprint classification is grouping the fingerprints that have similar patterns into the same category. The four categories of fingerprint are Left-loop, Right-loop, Whorl, and Arch Due to the noise in the fingerprint images, it is hard to classify them accurately. Therefore, it is necessary to develop a fingerprint classification method that implements a noise reduction technique.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview

In this chapter, a few noise reduction methods and fingerprint image enhancement methods are reviewed in order to understand their respective functionalities as well as their strengths and limitations. This section is ended with a summary by listing and comparing among all the methods reviewed.

2.2 Noise Reduction

2.2.1 Wavelet Transform

One of the methods on noise reduction is Wavelet Transform. Wavelet Transform is a type of linear transformation. It is very similar to the Fourier Transform but with a completely different merit function. Devnath et al. (2015) claimed that wavelet transform provides an accurate image of the quasi-harmonic components' dynamics in the form of signal. A wavelet is able to perform multi-resolution analysis and process data at different resolutions and scales. Thus, the multi-resolution analysis of the wavelet has benefits in space domain and also frequency domain. Wavelet analysis is widely used in image processing, video image compression, bio-medical engineering and other fields. According to Devnath et al., the wavelet transform is one step ahead of Fourier transform when used in noise reduction due to the localization of wavelet method in both time and frequency, while Fourier transform is only in frequency.

Ashish, Rabindra and Bhabani (2012) also studied that image de-noising are categorised into two basic classes, which are spatial domain and frequency domain. One of the frequency domain techniques is the Wavelet Transform and it is very powerful in image processing. Ashish, Rabindra and Bhabani also claimed that Wavelet transform will remove the noise in images by thresholding only the wavelet coefficient. This can be done by keeping the low-resolution coefficients unaltered. In the results of their experiment, they found that the wavelet method is more effective than the traditional mean and median spatial transformation methods. The method also can perform noise reduction of fingerprint better than MATLAB wavelet function for

Gaussian noise. In order to deal with salt and pepper noise, it is better to use Median filter.

The equation below shows the equation of the wavelet transform.

$$wf(a,b) = \int_{-\infty}^{+\infty} f(t) \Psi\left(\frac{t-b}{a}\right) dt$$

Wavelet transform usually is defined in terms of "mother" wavelet Ψ and scaling function φ . Using wavelet transform on image results in the approximation, vertical, horizontal, and diagonal components can be analysed on the fingerprint image.

There are a few strengths of the Wavelet transform compare to other methods. Wavelet transform is able to perform multi-resolution analysis. Its localization in both time and frequency and is able to decrease or remove noise effectively. However, there is also a downside of this method, which it can sometimes be less efficient due to the redundancy and quantity of wavelets.

2.2.2 Median Filter

Another method that is used to de-noise fingerprint images is Median Filter. Median Filter is a non-linear digital filtering method. It is often used in removing noise from images. This noise reduction process is a pre-processing step to enhance the image's quality. Median filter is widely used in digital image processing. According to Chandra and Kanagalakshmi (2011), Median Filter will reduce the blurring of edges in fingerprint images. The method is to replace the blurred point in the image by the median of the brightness in its neighbourhood. They also claimed that noise will not affect the brightness median in the neighbourhood and therefore the median smoothing will effectively eliminate impulse noise. In their experiment, the median filter method was applied and the result they got was the quality of median filtered fingerprint images improved. Figure 2.1 shows the example images before and after noise reduction using median filter.



Figure 2.1 Fingerprint image before and after noise reduction with Median Filter (Chandra and Kanagalakshmi, 2011)

On the other hand, Lu and Chou (2012) also proposed an improved directionalweighted-median (DWM) filter. The process of the method is as follow. First a noisecorrupted image will be analysed by a 7x7 sliding window. The centre pixel will be categorised to noise-free group and is kept unchanged to maintain the quality of the image if the centre pixel value in a local window is not an extreme value (0 or 255). Otherwise, the centre pixel will require to be further categorised until it becomes a noise pixel or an edge pixel. The pixel will be kept unchanged if the centre pixel is an edge. On the contrary, it will be considered as a noise pixel and should be changed by the directional-weighted-median (DWM) filter. Extreme value (0 or 255) will be excluded before undergoing the filtering. This will able to remove salt-and-pepper noise completely. The local window moves from left to right and up to down in an image until all pixels have been filtered. The process will also include noise detection and the modified DWM filter in order to remove impulse noise effectively.

The Strengths of the median filter is able to preserve the edges of the objects in images while removing the noise. It is also very effective when used to reduce impulsive noise, such as speckle noise and salt-and-pepper noise. However, the limitation of this method is that the method must process every entry in the signal, which sometimes makes it inefficient when dealing with large signals. Besides, the performance of this technique might not be good for high levels of noise.

2.2.3 Morphological operation

Besides, morphological operation is another method that can be used to reduce the noise of fingerprint images. According to Joy & Hemalatha (2018), morphological operators utilise the structural elements, such as dilation and erosion to determine whether the pixels beside each other is in the same region. Morphological operation is one of the widely accepted methods in fingerprint pre-processing. In the paper reviewed, morphological operators execute a binary dilation by a structuring element to combine small areas of fingerprint ridge regions. The binary dilation algorithm is given as below:

$$S_d = (S \oplus B)$$

= {z : z = s + b for some s \in S and b \in B}
= $\bigcup_{b \in B} (S)_b$

where B is the structuring element and S_d is the dilated image.

Then, fake regions that formed as background is being removed after the dilation process by filling in the holes in the image. Binary erosion is carried out after that using the same structuring element B. The binary erosion algorithm is given as below:

$$S_e = (S_d \ominus B)$$

= {z: B + z \le S_d}
= $\bigcap_{b \in B} (S)_{-b}$

where S_e is the eroded image.

The final step is to remove the areas which have an area (A) that is less than a threshold value to segment the fingerprint foreground region.



Figure 2.2 Before and after applying morphological operation

(a) Before Morphology, (b) After Morphology (Joy & Hemalatha, 2018)

There are some advantage and disadvantage of this morphology operation method. The advantage of using morphology operation is it produces binary images, which is an image with only black and white colours, instead of producing a grey scale image. Using binary image will results in faster execution time. Smaller memory is required with the use of binary images. The drawback of morphology operation is mainly due to it producing binary images, which has limited application to many situations.

2.3 Fingerprint Classification

2.3.1 Henry's Classification System

Fingerprint classification is the process of grouping fingerprints with the similar patterns into the same category. There are many fingerprint classification methods that based on different approaches. According to Harling et al. (1996), the Henry Classification System is the most commonly used fingerprint classification system. In Henry classification, each finger is assigned a number according to the order that the finger is located in the hand, starting from the right thumb as 1 to the left pinky as 10. Then, it assigns an alpha-numeric code to each fingerprint that is corresponding to one of two of the primary categories, in this case is the whorl and not-whorl. An example is shown in the figure below. In the figure, the value for fingers 1 and 2 is 16, value for fingers 3 and 4 is 8, and at last, finger 9 and 10 having the value of 1. Fingers with loop and arch pattern will be assigned the value of 0.

Table 2.1 Table of finger with assigned numbers and value (Harling, 1996)

	L Pinky	L Ring	L Middle	Lindex	L Thumb	R Thumb	R Index	R Middle	R Ring	R Pinky
Finger#	10	9	8	7	6	1	2	3	4	5
Value (if whorl)	1	1	2	2	4	16	16	8	8	4

The primary grouping of the fingerprint is identified by the ratio of 1 plus the sum of the values of the fingers having a whorl patterns with even number, divided by one plus the sum of the values of the fingers having a whorl patterns with odd number. The formula is described as below.

Henry Classification Formula: $\frac{1+(Sum \ of \ whorl, \ EVEN \ value)}{1+(Sum \ of \ whorl, \ ODD \ value)} = Primary \ Grouping$ Ratio

(2.2)

If an individual have no finger with whorl pattern, their classification would be 1:1. If an individual has 10 fingers with whorl patterns, the classification ration would be 31:31. Therefore, the Henry classification system can allow up to 1024 primary grouping, or distinct classifications. However, Levison et al. (1995) claimed that fingerprints that correspond to some of the 1024 classifications seldom appear and some classifications are extremely common. In U.S., a primary classification in any file categorized by the Henry System probably contains 25% of all the cards (refers to the table in Table 2.1) in the file. Thus, it is necessary to further subdivide the file. In recognition of this fact, Henry classification system provided three further levels of subdivision, which are the secondary classification, sub-secondary classification and major division.

At secondary classification level, fingerprint cards in the same primary grouping are subdivided based on their index fingers' pattern. Index fingers are classified into one of the five patterns. That means each primary grouping can be divided into 25 secondary classifications. At sub-secondary classification, fingerprint cards in the same primary and secondary classification are grouped based on three fingers, middle, ring and index fingers. This means that each secondary classification can be further divided into 81 sub-secondary classifications. At major division, fingerprint cards in the same primary, secondary, and sub-secondary classifications are grouped based on three fingers in the same primary. This means that each sub-secondary classifications are grouped based on thumbs' pattern. This means that each sub-secondary classification can be further divided into 12 major divisions.

There are certain drawbacks of using Henry classification system. First of them is the classification process consumes time, increases labour costs and also decreases productivity. Besides, the complex rules also increase the risk of misclassification, which leads to the increase of missed identifications. The only strength of the Henry classification system is that it is easy to use and does not require any special equipment.

2.3.2 Fourier Transform

The next fingerprint classification technique is a frequency domain based classification technique, which is the Fourier transform. Mostafa (2008) claimed that some Fourier transform methods failed to achieve a good outcome and also having the problem of overlapping between classes. Therefore, Mostafa (2008) proposed a method that is based on the Fourier transform which is used in multi-blocks or sub-image for fingerprint image that is produced by image segmentation as shown in the figure below.



Figure 2.3 Proposed frequency domain representation technique (Mostafa, 2008). (A) – The segmentation of fingerprint image and (B) – Frequency domain representation of (A)

The implementation of Fourier transform on sub images is important due to the fact that direction of ridges and frequency of the fingerprint image are not constant and varies from one block to another. This is to produce the pattern of each class, and it is a very accurate idea that could produce a better result to perform the procedure of fingerprint classification. The frequency components for each sub images are unique to each category of the fingerprint classes.

The proposed technique is to calculate a pattern for each fingerprint classes as shown in Figure 2.4 below. Then, these patterns are matched with every image of the fingerprints.



(A)





Figure 2.4 Patterns of the four fingerprint classes (A) – Arch, (B) – Left Loop, (C) – Right Loop, (D) – Whorl (Mostafa, 2008)

The block diagram of the proposed fingerprint classification algorithm that consists of the following steps:

- Fingerprint image input
- Divide fingerprint image into four sub-image by segmentation
- Calculate frequency domain for each sub image using Fourier transform
- Calculate the patterns for each class
- Match the calculate patterns
- Make decision based on pattern matching score



Figure 2.5 Flowchart of proposed classification method (Mostafa, 2008)

The strength of this classification method is it requires only a small amount of processing time. It also results in good performance and produces better results. It also works well when the true singular points are missing or the false one is exists. The main drawback of this method is the segmentation part processes the images as four separated images which caused the limitation of ridge directions to specific one.

2.3.3 Support Vector Machine

There is another classification method known as the Support Vector Machine (SVM). According to Wankhede & Doye (2005), SVM is a learning system that utilise hypothesis space of linear functions in a high dimensional feature space. SVM is also trained with a learning algorithm from optimization theory by applying a learning bias that is derived from statistical learning theory. SVM is a binary classifier. It is used to construct a decision boundary by mapping data from the original input space to a high dimensional feature space. Then only the data can be separated using linear hyperplane. As SVM is just a binary classifier, it cannot be used to handle the real world classification. In order to handle real world classification problem with multiple classes, a few methods are proposed in literature. According to Wankhede & Doye (2005), some examples of the proposed methods are One vs One, One vs Rest, DAGSVM and Error-correcting Code. For pattern recognition such as handwritten digit recognition, text categorisation and bio-informatics, SVM have been successfully implemented in these.

Wankhede & Doye (2005) also claimed that he binary classification of SVM is separated into three methods, linearly separable, linearly non-separable and non-linear.



Figure 2.6 Binary Classification Problem (Wankhede & Doye, 2005)

For example, given a data set A: $\langle x_1, y_1 \rangle$, $\langle x_2, y_2 \rangle$, K, $\langle x_i, y_i \rangle$. The purpose is to construct a classifier with decision function, f(x) such that it predicts the class of the data and minimizes the error of classification.

Since fingerprint classification is a multi-class classification, the literature review for this paper will be mainly focused in the multi-class classification section in this paper that is reviewed. Wankhede & Dove claimed that there are two main methods for k class classification, One Vs One Classifier and One Vs All Classifier. One Vs One Classifier or the pairwise classifier constructs k (k-1)/2 pairwise binary classifiers. The

decision of the classification is carried out by forming and grouping the outputs of the pairwise classifiers. Another multi-class classification method is known as the One Vs All Classifier. This method of classification trains k number of binary classifiers. Each of the k classes separates one class from other (k-1) classes. In this classification method, creation of model is done by assigning the label "+1" to c_i , and "-1" to all the other classes. The decision function of the SVM is as below:

$$f(x) = \sum_{i} \alpha_{i} y_{i} k(x_{i}, x_{j})$$

where $y_i \in \{-1, +1\}$

The class that maximizes the value of the above equation will be taken, resulting in the equation below:

$$f_{1VSR}(x) = \arg\max_{i} (f_i(x)) \quad i = 1, K, k$$

where $f_i(x)$ is the SVM model separating the ith class from the remaining classes.

There are some advantages of using SVM. First of all, SVM works well when there is a clear margin that separates classes. SVM is also more effective in high dimensional spaces. SVM also requires less memory. However, the drawback of using SVM is the algorithm of SVM is not suitable for large datasets. Besides, SVM does not perform well when there is more noise in the dataset.

2.4 Chapter Summary

Three noise reduction methods were compared and their strength and limitation were listed in Table 2.2 below.

Method Name	Wavelet Transform	Median Filter	Morphological Operations
Strength	• Able to perform multi-	• Able to preserve the edges	Produce binary image
	resolution analysis.	of the objects in images	(black and white) instead
	• Able to decrease or	while removing the noise.	of grey scale image.
	remove noise effectively.	• Very effective when used	• Faster execution time
		to reduce impulsive noise,	• Smaller memory required
		such as speckle noise and	
		salt-and-pepper noise.	
Limitation	Can sometimes be less	Must process every entry	• Limited application, not
	efficient due to the	in the signal, which	applicable to many
	redundancy and quantity	sometimes makes it	situation
	of wavelets.	inefficient when dealing	
		with large signals.	
		• Performance of this	
		technique might not be	
		good for high levels of	
		noise.	

Table 2.2 Comparison of three noise reduction methods

Three fingerprint classification methods were compared and their strength and limitation were listed in table 2.3 below.

Method Name	Henry Classification	Fourier Transform	Support Vector Machine
Strength	• Easy to use and does not	• Requires only a small amount	• Works well when there is a
	require any special equipment.	of processing time.	clear margin to separate
		Good performance and	classes.
		produces better results.	• More effective in high
		• Works well when the true	dimensional spaces.
		singular points are missing or	Requires less memory
		the false one is exists.	
Limitation	Classification process	Segmentation part processes	Not suitable for large
	consumes time, increases	the images as four separated	datasets.
	labour costs and also	images which caused the	• Does not perform well when
	decreases productivity.	limitation of ridge directions	more noise exist.
	• The complex rules also	to specific one.	
	increase the risk of		
	misclassification, which leads		
	to the increase of missed		
	identifications.		

Table 2.5 Comparison of three ingerprint classification methods	Table 2.3	Comparison	of three fin	gerprint o	classification	methods
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CHAPTER 3: Method Design

3.1 Methodology

Figure 3.1 shows the flowchart of the development.



Figure 3.1 Flowchart of development

First of all, the dataset, which are the fingerprint images were pre-processed by using Morphological Gradient and Median Filter. This pre-processing step was to reduce the noise in the images. The processed images were saved as another set of image to use with the classification method. Next, the algorithm for the Support Vector Machine was developed using Python language in Jupyter Notebook. In the algorithm of Support Vector Machine, two different kernels were used, which are linear kernel and radial basis function (RBF) kernel.

During the experiment phase, the original fingerprint image set was first tested using the algorithm. The accuracy of the classification was recorded. Then, the pre-processed fingerprint image set was tested using the algorithm. The accuracy of the classification was recorded. The result of the experiment was analysed and discussed. Finally, conclusion was made based on the analysis and discussion of the result.

3.2 Design Specifications

In this project, a fingerprint image pre-processing method together with a fingerprint classification method is developed.

3.2.1 Pre-processing Method

In the experiment, two pre-processing methods were used. One of the methods is developed based on the morphological transformation method, while another method is the median filter method. The morphological transformation method can be used in noise reduction of fingerprint image. Morphological method produce binary image (black and white image) which required smaller memory and results in faster execution or processing time.



Figure 3.2 Example of original and pre-processed images

(a) Original image, (b) Morphological gradient (binary image), (c) Median filter

As explained in Section 2.2.3, there are several operations in morphological transformation. The two major operations are erosion and dilation. In erosion, the boundaries of the foreground of the image are eroded away, making the foreground thinner. Whereas in dilation, the boundaries of the foreground of the image are dilated,

the size of the foreground is increased, making the foreground thicker. When these two operations come together, it is called the morphological gradient. Morphological gradient is the difference between the erosion and dilation. This results in an image with the outline of the foreground.

On the other hand, the median filter works by checking each pixel in the image. When it is checking the pixels, it also checks its neighboring pixels to decide whether the pixel is an important pixel or not. Then it replaces the neighboring pixels by its median value to reduce noise in an image. The median is calculated by sorting the values of the neighboring pixels and replaces it with the middle pixel value.

3.2.2 Classification Method

The fingerprint classification method is developed based on the Support Vector Machine method. The type of Support Vector Machine used is the One Vs Rest classifier, also known as the One-Against-All classifier. Since fingerprint consists of many classes, One Vs Rest classifier is suitable to be used in this project since it is a multi-class classifier. The algorithm of One Vs Rest classifier works in a way that it needs the consensus among all the SVMs. This means that a data is clarified to a particular class if and only if the SVM of the class accepts it and all the SVMs of other classes reject the data (Aisen, 2006).

The algorithm of SVM uses a kernel that is defined by various mathematical functions. The function of the kernel is to transform the input data into the required form. The kernels are also used to map the dataset to form a higher dimensional space. Different kernels are different in generating the hyperplane between the classes. Hyperplane is the decision boundary that is generated to differentiate between classes. By using different kernels, the result of the experiment is expected to not be the same since different kernel generates different hyperplane.

3.2.3 Tools used

This project is developed in the Windows 10 operating system. The following software and tools were installed for the development:

Operating System	• Windows 10
Integrated Development Environment (IDE)	• Jupyter Notebook
Programming Language	• Python
Other	Internet Connection

Table 3.1 Tools used in development

3.3 Implementation Issues and Challenges

There are several issues and challenges during the development of this method. The first challenges are the exploitation of an unfamiliar field. Before developing the method, it takes a lot of effort of learning and exploring about the field. Several classification methods had been studied, review and compared.

Next challenge is using OpenCV, a programming library that I have never learned before. The OpenCV library has to be studied to know how it works in order to implement it inside my project.

Finally, the dataset of the fingerprint images that is found online has not been classified or categorised into their respective classes. Therefore, the images have to be studied and grouped manually. Furthermore, some images of the fingerprint contain noise, which caused problems and difficulties when classifying them.

Fingerprint Classification Using Support Vector Machine



Figure 3.3 Project Timeline

3.5 Chapter Summary

In this project, a fingerprint image pre-processing method together with a fingerprint classification method is developed. The pre-processing method used to reduce the noise of the fingerprint images is the morphological gradient method. Whereas the classification method used is the Support Vector Machine. Different kernel functions were also used to compare the result of the classifier.

CHAPTER 4: EXPERIMENT

4.1 Experiment Data

The dataset for this experiment is taken from the website https://www.kaggle.com/ruizgara/socofing. This dataset consists of 6000 fingerprints images taken from 600 African subjects. Each of the fingerprint images is named as left or right hand with the name of finger with the gender of the human. For example "100_M_Left_index_finger.BMP" means the fingerprint image is taken from the left hand index finger of a male.

The dataset is not classified into different categories. Therefore, a manual classification is done in order to prepare the dataset for the experiment. 500 fingerprint images are selected and classified into the four categories of fingerprints, whorl, arch, left loop and right loop. Then, 5 different datasets are formed, one dataset with 100 images (25 images in each category), and another one with 200 images (50 images in each category) and so on. Before the experiment, 80% of the images are selected from each dataset to be used as training set, while the remaining 20% are used as testing set. All the images are renamed to the format of [categorynumber]_[imagenumber]. There are four category numbers, 1 to 4, 1 refers to whorl, 2 refers to arch, 3 refers to left loop and 4 refers to right loop. For example 1_1.BMP means the image is the first image in the whorl category.

4.2 Experiment Details

4.2.1 Pre-processing

The pre-processing method used to reduce the noise of the fingerprint images is morphological gradient and median filter. The programming language used to develop this pre-processing method is Python and the Integrated Development Environment that is used is Jupyter Notebook. First, the OpenCV library is imported into the notebook. Next, the image files are being located and read. Images of the fingerprint are being processed by using morphological gradient. After that, the new processed images are saved into a different directory for later use in the classification method. These steps are repeated until all the images have finished processing. Both the training set and the testing set of images are being processed.



Figure 4.1 Before and after applying noise reduction method

(a) Without pre-processing, (b) Median filter, (c) Morphological gradient

Another pre-processing method is also applied in order to compare with the morphological gradient method, which is the median filter. Figure 4.1 shows the image of before applying pre-processing method using the two methods mentioned.

4.2.2 Classification

The classification method used is the Support Vector Machine (SVM). The programming language used to develop this pre-processing method is Python and the Integrated Development Environment that is used is Jupyter Notebook. The libraries needed in this development are imported into the notebook. First, the images files are read and the path for the training set and testing set have been set. The images are then resized to 256x256 pixels to get an equal matrix. Next, the training set and testing set are labelled as X_trainLabels and X_testLabels. For the actual classification, two different kernels were used, linear kernel and RBF kernel. The type of Support Vector Machine used is the One Vs Rest Classifier. The classifier is first tested with the original unprocessed images, and then the images that were processed using morphological gradient. The accuracy of this classifier was computed and recorded in a table.

Two testing have been done, an empirical test and cross validation. Empirical test was carried out to test the accuracy of the classification for the first time. In the empirical test, 20% fingerprint images with good quality were selected from their respective dataset as the testing set. The remaining 80% was used as training set.

Cross validation is carried out in classification by randomly selecting 20% of images from the dataset, and equal number of images from each class. For example, 20 random images (5 images from each class) were selected from a dataset having 100 images. The 20% of images are used as the testing set, while the remaining 80% of images are used

as training set. Then, these images were used in the classification algorithm mentioned in section 4.2.2. The accuracies were recorded. There are five groups of datasets in total, consisting of 100, 200, 300, 400, and 500 images respectively. Each dataset was iterated for 50 rounds.

4.3 Classification Results

4.3.1 Empirical Testing

Table 4.1 shows the empirical results of the experiment.

	Without Pro	e-processing	After A Morph Grae	pplying ological dient	After Apply Fil	ving Median ter
Dataset	Linear Kernel	RBF Kernel	Linear Kernel	RBF Kernel	Linear Kernel	RBF Kernel
80 training, 20 testing	55.00 %	60.00 %	50.00 %	55.00 %	45.00 %	60.00 %
160 training, 40 testing	65.00 %	70.00 %	52.50 %	70.00 %	55.00 %	75.00 %
240 training, 60 testing	53.33 %	61.67 %	36.67 %	68.33 %	48.33 %	71.67 %
320 training, 80 testing	57.50 %	61.25 %	47.50 %	70.00 %	43.75 %	60.00 %
400 training, 100 testing	51.00 %	63.00 %	43.00 %	71.00 %	43.00 %	69.00 %

Table 4.1 Results of empirical test

Five rounds of experiments were carried out. The first round was using a dataset with 100 fingerprint images and the second round was using a dataset with 200 fingerprint images, and so on. Each round of the experiment is also separated into three phases. The first phase is to use the original fingerprint images which are not pre-processed. The second phase is to use the pre-processed fingerprint images with morphological gradient. The third phase is to use the pre-processed fingerprint images with median filter. In the experiment, two different kernels were also used, which are linear kernel and RBF kernel. The result of the experiment is compared and analysed.

4.3.1.1 Pre-processing

Referring to table 4.1, in general, the accuracy of classification after applying median filter is better than the accuracy of after applying morphological gradient. The highest accuracy obtained in the experiment after applying median filter method is 75%. Whereas the highest accuracy obtained after applying morphological gradient is 70%. The lowest accuracy obtained is 43%, which is using linear kernel with both morphological gradient and median filter in 500 dataset. The overall accuracy of after applying morphological gradient is also lower than the accuracy of using original images in 100, 200 and 300 datasets. The accuracy of after applying morphological gradient is higher than the accuracy of after applying Median Filter in 400 and 500 datasets. The accuracy of after applying median filter with linear kernel of the classifier is lower than its counterpart result of using images without pre-processing.

4.3.1.2 Classification Kernel

Referring to table 4.1, all the classification accuracies of the RBF kernel is better than the linear kernel. Without any pre-processing method applied, the highest accuracy of the classifier is 70%. When using linear kernel, the result is slightly lower than their counterpart result of using RBF kernel.

4.3.1.3 Dataset Size

By just comparing the number of dataset used, the accuracy of the dataset with 200 fingerprints is higher than the accuracy of the dataset with only 100 fingerprints. Without pre-processing, the accuracy of using 100 dataset is 55% and 60% for linear and RBF kernel respectively while the accuracy of using 200 dataset is 65% and 70% for linear and RBF kernel respectively. There is a 10% increase in the accuracy. However, the accuracy decreases when dataset with 300, 400 and 500 was used.

4.3.2 Cross Validation Results

In Cross Validation, images that pre-processed using Median Filter were used. This is because the accuracy of after applying Median Filter in empirical test shown that it is better than the rest.

Table 4.2 shows the results of cross validation.

Dataset	Average Accuracy (Linear)	Average Accuracy (RBF)
100	42.50 %	56.70 %
200	43.25 %	57.00 %
300	39.83 %	47.17 %
400	40.35 %	49.05 %
500	41.00 %	49.82 %

Table 4.2 Results of cross validation

Figure 4.2, 4.3, 4.4, 4.5, 4.6 show the graph of accuracy against run for each dataset.



Cross Validation 100 Dataset

Figure 4.2 Graph of accuracy against run for 100 dataset



Figure 4.3 Graph of accuracy against run for 200 dataset



Figure 4.4 Graph of accuracy against run for 300 dataset



Figure 4.5 Graph of accuracy against run for 400 dataset



Figure 4.6 Graph of accuracy against run for 500 dataset

4.3.2.1 Cross Validation (Kernel)

Referring to table 4.2, the overall accuracy of RBF kernel is better than linear kernel. Accuracies of using linear kernel are slightly lower than their RBF accuracies counterpart. The highest accuracy of the Cross Validation process is 43.25% for linear kernel and 57% for RBF kernel. The lowest accuracy obtained is 39.83% for linear kernel and 47.17% for RBF kernel.

4.3.2.2 Dataset Size

By comparing average accuracy of each dataset, the average accuracy of the dataset with 200 images is the highest, which is 57%. The dataset that have the lowest average accuracy is dataset with 300 images, which is only 39.83%. Referring to the graphs from figure 4.2 to figure 4.6, the highest accuracy achieved in dataset 100 for RBF kernel is 80% and 65% for linear kernel. Both accuracies are higher than their corresponding accuracies obtained in empirical test. Meanwhile, the lowest accuracy achieved in dataset 100 for RBF kernel is 35% and 15% for linear kernel. For dataset 200, by referring to the graph in figure 4.3, the highest accuracy achieved for RBF kernel is 67.5% and 47.5% for linear kernel, while the lowest accuracy achieved for RBF kernel is 40% and 35% for linear kernel. By referring to figure 4.4, the highest accuracy achieved in dataset 300 for RBF kernel is 63.33% and 53.33% for linear kernel, while the lowest accuracy achieved for RBF kernel is 31.67% and 26.67% for linear kernel. For the graph in figure 4.5, which is dataset 400, the highest accuracy achieved for RBF kernel is 56.25% and 48.75% for linear kernel, while the lowest accuracy achieved for RBF kernel is 37.5 and 30% for linear kernel. Lastly, by referring to figure 4.6 for dataset 500, the highest accuracy achieved for RBF kernel is 63% and 48% for linear kernel, while the lowest accuracy achieved for RBD kernel is 34% and 32% for linear kernel.

4.4 Chapter Summary

In this chapter, the results of the method developed in Chapter 3 are shown. The general accuracy of the median filter is higher than the accuracy of morphological gradient. For kernel, the RBF kernel has higher accuracy compared to linear kernel. However, the overall accuracy is not good as the images are selected and classified manually. The accuracy of cross validation is also recorded.

CHAPTER 5: DISCUSSION

5.1 Discussion for Pre-processing

For dataset 100 and 200, the overall result of the accuracy of using median filter is higher than the accuracy of using morphological gradient. This shows that median filter is more effective in reducing the noise in fingerprint images. This is because the median filter checks every pixel and their neighboring pixels. Then it computes the median value for a pixel. This will help to preserve the important pixels or details in the image while reducing the noise of the image.

The results shows that with morphological gradient applied, the accuracy is lower than the accuracy of classification of original images with no pre-processing method. This shows that morphological gradient might not be suitable to be used to reduce the noise in fingerprint images. This is because some important details might have lost during the pre-processing step. By referring to figure 4.2, the broken ridges are not joined together after applying morphological gradient. Besides, the overall shape of the shape of the fingerprint of figure 4.2(b) is preserved after applying median filter, which the shape is clearer than figure 4.2(c).



Figure 5.1 Comparison between original and pre-processed image

(a) Without pre-processing, (b) Median filter, (c) Morphological gradient

But for dataset 300, 400 and 500, the accuracy is lower than dataset 200. This is probably because the images of dataset 200 is among the best images in the whole dataset that was taken from the database. Whereas for dataset 300, 400 and 500, images with lower quality was added to the dataset. This caused dataset 100 and 200 having images with higher quality than images from dataset 300, 400, and 500. Therefore, causing the accuracy of dataset 300, 400, and 500 to be lower than the accuracy of dataset 100 and 200.

5.2 Discussion for Classification

The result of the experiment shows that all the accuracy of using RBF kernel is higher than the accuracy of using linear kernel. This is because linear kernel usually is used when there is a clear and linear class boundary. It is normally used in classification that involves only 2 classes. While in this experiment, there are four classes of fingerprints. In this case, RBF kernel is more suitable to be used to classify the four categories of fingerprints because RBF kernel is normally used when the class boundaries are not linear. Therefore, the accuracy of using RBF kernel is higher than the accuracy of using linear kernel.

However, the overall accuracy of the method is not very good. The reason behind this is due to the fingerprint images were being selected and classified manually by human. Some selected fingerprint images may have worse noise compared to other images.

In dataset 100, high accuracy (80%) is able to achieve as the images are manually selected and they have the best quality compared to others. Whereas for dataset 300, 400 and 500, new images were added. The new images do not have the same quality as in dataset 100, therefore causing the accuracy to be lower. Most of the accuracy falls on the range of 40% to 60%, by referring to section 4.3.2.

5.3 Discussion for Size of Dataset

The result also shows that the accuracy of the dataset with 200 fingerprints is higher than the accuracy of the dataset with 100 fingerprints in all situations. This is because when the number of dataset increases, there is more information during the training of the machine to learn. When the machine learns more about the dataset, the prediction will be more precise. Therefore, this caused the accuracy to increase when the size of dataset increases.

However, for dataset with 300, 400 and 500 fingerprints, the accuracies did not increase with the increased number of training images. This is probably caused by the images with lower quality being added to the dataset.

5.4 Discussion for Cross Validation

The accuracy of the cross validation is showing the same pattern as the result of classifications, where dataset with 200 images having the highest accuracy, and dataset 300, 400 and 500 are having lower accuracy than dataset 100 and 200.

However, the results shows a trend where the accuracy increases with the increased number of images in dataset.

From figure 4.2 to figure 4.6, the graphs show that some of the accuracies for the RBF kernel is higher than the accuracy to its corresponding empirical testing result. This means during the random selection process in the cross validation, better fingerprint images were selected for the testing set, and thus causing the accuracy to be higher.

5.5 Chapter Summary

In this chapter, the results shown in Chapter 4 are analysed and discussed. The accuracy for dataset 100 and 200 is consistent, but not for dataset 300, 400 and 500. The overall result of using RBF kernel is higher than the accuracy of using linear kernel.

CHAPTER 6: CONCLUSION

6.1 Conclusion

Fingerprint recognition is a good identification method. However, it is slow when there is a huge database. Classification of fingerprints is required to reduce the search time in the database. The problem of classification was discussed in chapter 1. Meanwhile, several noise reduction methods and fingerprint classification methods were studied and reviewed in chapter 2.

Among all the programming language, python language was selected as the programming language to develop this method. Jupyter Notebook was also selected to be the integrated development environment. The details of proposed method, design specification and the challenge faced were also discussed in chapter 3. The experiment results and discussion were also discussed in chapter 4.

Throughout this experiment, not all noise reduction methods or classification methods are suitable to use with the classification of fingerprints.

6.2 Future Work

The classification algorithm will be enhanced to improve the accuracy of classification. Next, a cleaner, classified dataset also has to be used for a better accuracy. A different noise reduction method also will be implemented. Furthermore, a pre-processing method that recovers the broken ridges in fingerprint images will also be implemented.

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APPENDIX

Original Image	Median Filter	Morphological Gradient

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Original Image	Median Filter	Morphological Gradient

POSTER

Science (HONS)



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