EMBEDDED FINGER VEIN RECOGNITION SYSTEM USING RASPBERRY PI WITH IMPROVED REGION OF INTEREST

LIM YUAN ZHANG

UNIVERSITI SAINS MALAYSIA

2017

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By

LIM YUAN ZHANG

Thesis submitted in fulfilment of the requirements for the degree of Bachelor of Engineering (Electronic Engineering)

JUNE 2017

ACKNOWLEDGEMENTS

First of all, I would like to express my deepest gratitude to my final year project supervisor, Associate Professor Dr. Bakhtiar Affendi Bin Rosdi. He had provided much useful insights, teachings and advices whenever necessary. Despite being busy at times, he still managed to keep track on my progress and even set up discussion session to give me as much help as possible. My final year project wouldn’t be completed successfully if it weren’t for him. It is indeed my privilege to be under his supervision.

Furthermore, I would like to extend my sincere gratitude to my friends, course mates and students from class conducted by Associate Professor Dr. Bakhtiar who voluntarily contribute their finger information for the completion of my project. I would also like to thank my friends and family who helped or encouraged me throughout my final year project.

Last but not least, I had received support from too many people to count during my project development. Though not all names are mentioned in black and white, I would like to say that their various contributions have not gone unnoticed or unappreciated.

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List of Abbreviation

FV	Finger Vein
FVRS	Finger Vein Recognition System
IR	Infrared
NIR	Near Infrared
NoIR	No Infrared
ROI	Region of Interest
RPI	Raspberry Pi

List of Symbols

a	Gradient of line
i	Row
j	Column
x	Point x in horizontal x-axis
x_{ft}	Point x of fingertip in horizontal x-axis
Δx	Difference between x_{ft} and x
y	Point y in vertical y-axis
y_{ft}	Point y of fingertip in vertical y-axis
Δy	Difference between $y_{ft}\ and\ y$
S_p	Sliding window
w	Width
r_1	Position of the distal inter-phalangeal joint
r_2	Position of the proximal inter-phalangeal joint
d_1	Distance between r_1 and r_2,
d_2	Distance from r_2 to the last row of the image
θ	Skew angle in radian
$\propto$	Skew angle in degree

SISTEM PENGECAMAN URAT JARI TERBENAM MENGGUNAKAN RASPBERRY PI DENGAN PENAMBAHBAIKAN KAWASAN KEPENTINGAN

Abstrak

Sistem Pengecaman Urat Jari (FVRS) ialah teknologi biometrik yang mengenal pasti individu berdasarkan corak urat yang unik. Prestasinya ditentukan oleh keteguhan perkakasan dan perisian. Berdasarkan analisis FVRS sebelum ini, pembangunan perisian menghadapi masalah imej pra-pemprosesan terutamanya dalam pengekstrakan kawasan kepentingan (ROI). Ini adalah kerana FVRS sebelum ini menggunakan cara tingkap empat segi yang bersaiz tetap untuk mengekstrakkan ROI. Kaedah ini mengabaikan unsur salah letak jari dan tidak mengekstrak ROI berdasarkan rujukan umum. Objektif projek ini adalah untuk meningkatkan ketepatan FVRS sebelum ini dengan membetulkan imej FV yang tidak sejajar dan mengekstrak ROI berdasarkan rujukan umum. Secara keseluruhannya, projek ini menyumbang kaedah yang baru untuk segmentasi imej urat jari menggunakan segmentasi tadahan air dengan jarak mengubah, mengadaptasikan kaedah bagi membetulkan orientasi imej jari dan mengekstrakkan ROI secara konsisten menggunakan tetingkap gelongsor tunggal berdasarkan sendi pelana jari. OpenCV dan bahasa perisian C++ telah digunakan dalam projek ini. Keputusan menunjukkan bahawa sistem yang dimajukan mampu menyelaraskan imej jari tanpa mengira penempatan jari semasa pendaftaran dan verifikasi serta mendapat ROI berdasarkan sendi pelana jari. Penilaian prestasi menunjukkan bahawa ketepatan sistem yang dimajukan mencapai 89.33%, peningkatan sebanyak 37.66% berbanding dengan FVRS sebelumnya.

EMBEDDED FINGER VEIN RECOGNITION SYSTEM USING RASPBERRY PI WITH IMPROVED REGION OF INTEREST

Abstract

Finger Vein Recognition System (FVRS) is a biometric technology that identifies or verifies an individual based on unique vein patterns. Its performance is determined by the robustness of hardware and software development. According to the analysis of original FVRS, the software development stumbled upon image pre-processing stage particularly in the extraction of region of interest (ROI). The reason to the failure was because of the use of fixed window ROI extraction method, where the ROI was extracted using a predefined rectangle window. This method disregards the misplacement of finger and has no common reference point in extracting ROI. The objective of this project is to improve the accuracy of original FVRS by correcting the orientation of misaligned FV image and extracting ROI based on localised benchmark. In overall, this project contributed a new method of finger vein image segmentation using watershed segmentation with distance transform, then applied adapted methods to correct finger image orientation and extract consistent ROI using single sliding window based on phalangeal joints. OpenCV image processing library and C++ language were used in the development. The results proved that the improved system is able to correct the orientation of finger image regardless of finger placement during enrolment and verification, as well as obtaining ROI based on phalangeal joints. The performance evaluation shows that the verification accuracy of the improved system achieved 89.33%, an increase of 37.66% compared to original FVRS.

CHAPTER 1

Introduction

1.1 Research Background

The term biometric refers to the measurement of human physical traits and behavioural traits. Several common physical traits used in biometric technologies are fingerprints, palmprints, face, iris while behavioural traits used are voice and gait (Hsia et al. 2017). Biometric technologies are widely used in various identity authentication and verification applications, namely customs, airports, banks and so on (Pham et al. 2015).

Personal verification can be achieved using traditional password-based authentication system. However, it is vulnerable to the risk of exposure and being forgotten. Thus, biometric technologies have been extensively researched and developed so as to meet the high demand for information security (Parthiban et al. 2014). Of all biometrics developed, fingerprint recognition system is the most established biometric technology where many applications can be seen utilising this system. Despite being the most common approach these days, fingerprint recognition system still poses risk of forgery due to the exposure of fingerprints easily. It also degrades the system's performance when it comes to obtaining unclear fingerprint images due to sweat or dry condition (Rosdi et al. 2011). On the other hand, palmprints, like fingerprints, is also easily replicated since the features extraction are from the external of human body. Both palmprints and fingerprints are considered less hygienic as they require physical contacts (Shahrimie et al. 2014). Besides, biometrics such as face, iris and fingerprints are susceptible to spoofing attacks in which biometric identifiers are copied to create artifacts that deceive the system (Raghavendra & Busch 2015).

In response to the addressed drawbacks of several biometrics, researchers have put considerable attention to personal authentication using finger vein (FV) biometric identifier (Dong et al. 2015). This is because finger veins are hidden under the skin and therefore it is almost impossible to be forged. It also provides extremely high security due to its distinctive patterns that no one finger, even twins or our own fingers have the same vein pattern. Moreover, finger vein pattern can only be obtained from a living person (Qiu et al. 2016). It also proves to be more hygienic as the authentication uses Near Infrared Light (NIR) rather than placing the finger on a surface (Van et al. 2016; Chandra et al. 2014). Lastly, finger vein biometric is usually low cost and smaller in size (Xie et al. 2015). Due to these characteristics of increased security and reliability, finger vein biometric outperforms other biometric identifiers.

Typically, biometric recognition follows three stages. Poor performance in any stage will heavily impact the functionality and accuracy of biometric recognition. Finger Vein Recognition System (FVRS) is no exception. The three stages involved are:

1. **Image acquisition:** Image acquisition in FVRS exploits the fact that the absorption of light in near infrared (NIR) and infrared (IR) wavelengths by different human tissues produces unique vein images (Vlachos & Dermatas 2015). Pre-processing and post-processing can solve some low-quality problems. However, if image quality is too low, simple postprocessing can hardly solve the problems (Liu et al. 2016).

2. **Pre-processing:** It is a crucial process in the whole verification system. The main steps include edge detection, alignment and ROI extraction (Shahrimie et al. 2014).

3. **Feature extraction & matching :** Feature extraction transforms the input data into a set of features with relevant information for the matching in verification (Kumar & Bhatia 2014). It is also the core step of FVRS as it determines the performance greatly in recognition accuracy and processing time (Liu et al. 2016).

Robustness of these three stages contribute to developing a high quality FVRS. Out of the three stages, pre-processing stage is considered as one fundamental stage that extracts and reserves important information for the better process development in next stages. As pre-processing quality affects the other stages heavily, this project thus aims to improve original FVRS in the pre-processing stage by correcting orientation of FV image and extracting consistent ROI based on localized benchmark.

1.2 Problem Statement

After finger vein image is obtained at image acquisition stage, image pre-processing takes place first before further enhancement, feature extraction and matching. It is worth to mention that in pre-processing stage, it is important to extract good ROI. ROI of a finger vein image refers to the region of finger which is filled with abundant finger vein pattern. The aim of ROI extraction is to decide which part of the image is fit for finger vein feature extraction, thereby reserving the useful information in the ROI and removing the useless information in the background (Yang et al. 2013).

In order to extract good ROI, two steps are involved, the (i) orientation correction of FV image and (ii) localization and extraction of ROI. The original FVRS system failed to perform well in the pre-processing stage where region of interest (ROI) is extracted while FVRS developed by Leong (2016) focused only on image enhancement and classification. The neglection on image pre-processing had the performances greatly reduced (Leong 2016).

Before extraction of ROI, orientation correction of FV image is a must because more often than not the images acquired are skewed, which means the finger vein image are either slanted to the left or right, but not entirely straight. If the skewed images are enrolled into the database, users will have to adjust their finger positions to fit the image for correct verification as they may position their fingers differently compared to the placement during image enrolment. In other words, skewed finger vein images cause the FVRS to be sensitive to finger position variation (Lu et al. 2013).

Followed by the orientation correction is the localization and segmentation of ROI. Images captured are usually associated with unwanted noise such as the presence of light source illumination and the reflection of light on the edge of image acquisition device (IAD). An accurate ROI extraction removes useless information in the background and preserves consistent referential information that will significantly improve the performance in FVRS (Yang et al. 2013).

Original FVRS did not correct the orientation of FV image and failed to obtain a stable ROI. It extracts ROI by just cropping FV image with a fixed rectangle, which means it lacks a consistent localized benchmark. Without localized benchmark, the ROI is considered unstable and sensitive to finger displacement. This is because the information varies largely between the enrolled image and verifying image every time users insert their fingers at different position.

For orientation correction, the FVRS proposed Yang et al. (2013) and Yang et al. (2015) corrected the skewed image by finding the midpoint of finger edges and synthesise an equation of straight line. The slope coefficient was then obtained to calculate angle for orientation correction. This method is able to solve only orientation problem caused by planar rotation but not space rotation. For that, Qiu et al. (2016) proposed a pseudo-elliptical sampling model to transform the FV image in feature extraction stage to reduce the image differences of the same finger at different acquisitions caused by space rotation of the finger. This method is able to reduce the differences of FV patterns caused by space rotation but is a more complex.

For ROI extraction, Shahrimie et al. (2014) had proposed a method that extracts ROI based on fingertip and width centroid contour distance. However, this method constrains the placement of the user's fingertip since the entire finger with fingertip should be acquired. Yang & Shi (2012) suggested that the phalangeal joints of the finger provides useful information because it allows more light to penetrate when an NIR LED is placed over a finger, and a brighter region may exist in the image plane. Yang et al. (2013) also exploit the properties of phalangeal joints to extract ROI images by using single sliding window localization and is more effective than the method in Yang & Shi (2012). However, both methods are susceptible to light interference. In the FVRS proposed by Qiu et al. (2016), dual sliding window localization estimates the position of phalangeal joints more accurately by eliminating light interference. Nevertheless, this method is not able to locate phalangeal joints correctly under severe illumination or overly uneven illumination along finger. Moreover, it takes longer computational time as it calculates sum of gray value and subtraction of two windows instead of one window. Therefore, it is not necessary to use this method if FV image is not affected by uneven illumination.

1.3 Objectives

The objective of this project is to improve the accuracy of verification by:

i. Acquiring properly aligned finger vein images regardless of the placement of finger.

ii. Obtaining consistent and well-defined ROI images based on localized benchmark.

1.4 Scope of the Project

The finger vein recognition system's (FVRS) main function in this project is verification, which is to verify a person's identity based on the individual's finger vein patterns. The scope of this project is to improve the original FVRS in terms of verification accuracy. This was done by targeting the development in image pre-processing stage.

This project's first focus was on the software development before feature extraction takes place, that is to correct the misaligned or skewed finger vein image so that the verification is not affected by finger position. Prior to orientation correction, several steps are taken to segment finger image and obtain clear finger edges. The second focus was also on the software development. Right after orientation of FV image is corrected, the ROI of finger vein image is obtained based on two reference points, in this case, the phalangeal joints. After that, the ROI was used for matching by using previous method. Eventually, the performance of the improved system was compared with the previous system by testing them with the same image database.

1.5 Thesis Outline

The following chapters of this thesis are chapter 2 to chapter 5. Chapter 2 presents the literature review on the ROI extraction methods used by recent finger vein recognition system. Chapter 3 describes the methodology of this project. The methods and steps of correcting orientation of FV image and extraction of ROI will be thoroughly explained in this chapter. Chapter 4 shows and discusses the result and performance of the improved FVRS, as well as its comparison with original FVRS. Chapter 5 concludes the project in overall. The limitation and future work regarding this project are stated clearly in this chapter.

CHAPTER 2

Literature Review

2.1 Introduction

The embedded FVRS using raspberry pi is a verification system based on finger vein patterns. It runs on a microcomputer board known as raspberry pi (RPI) and integrates with the image acquisition device (IAD). IAD is used to capture the finger vein image of subject by using NIR laser line modules as light source and RPI No Infrared (NoIR) camera as IR sensitive camera. RPI further process the captured image for verification purpose by running the software.

In the aforementioned chapter, the development of FVRS includes 4 stages: the image acquisition, pre-processing, feature extraction and verification. Image acquisition stage as described above deals with hardware, while the rest of 3 stages are solely software development. This project emphasizes on the software development in image pre-processing stage, particularly in the pre-extraction and extraction of ROI. The following sections present the introduction to FV recognition and different ROI extraction methods. Algorithms of various ROI extraction methods were also discussed.

2.2 Introduction to Finger Vein Recognition

FVRS has emerged as a promising biometric system in the recent years. It receives wide attention and has achieved remarkable development during the last decade. This is mainly because FVRS proves to provide more advantages over traditional biometric systems (Xie et al. 2015). Among the advantages are:

1. **Anti-counterfeit**: Finger veins are located underneath the skin. It is nearly invisible to human eyes under normal lighting, making it practically impossible and improbable to be duplicated (Chandra et al. 2014).

2. **Uniqueness**: Vein patterns are distinctive between twins and even between a person's left and right hand. Its shapes also vary little in regard to a person's growth (Sugandhi et al. 2014).
3. **Active liveness**: Finger vein pattern can only be obtained from a living person (Qiu et al. 2016). The veins are viewable with reflected light due to the peak absorption of near infrared illumination by oxygenated and de-oxygenated haemoglobin in the blood (Xie et al. 2015). Therefore, it can be said that vein information is present when the person is alive, and absent otherwise. This makes artificial veins unavailable in application.
4. **User friendliness**: Finger vein images can be captured noninvasively without the contagion and unpleasant sensations. The contactless finger veins recognition ensures both convenience and hygiene for the user (Yang & Shi 2012).

With these advantages over traditional biometric systems and the increasing demand in higher levels of data protection, the FVRS is being developed and researched rapidly (Parthiban et al. 2014). Its applications can be seen in wherever security is concerned such as military zones entry, confidential sectors, automated teller machines and many more (Sugandhi et al. 2014).

The FVRS has three main modules: IAD, image processing module and verification module. IAD captures FV image by using NIR light and IR light sensitive camera. Image processing module pre-processes the raw FV images acquired by correcting alignment of image and extracting good ROI. Then it further processes the ROI by extracting unique feature of the veins. Lastly, the verification module matches an individual based on the extracted feature vectors.

2.3 ROI Extraction

Extraction of ROI is extremely important in FVRS to obtain image containing useful finger vein information. It must be consistent in the enrolment and verification process. Several methods had been proposed to extract ROI from FV images:

2.3.1 Fixed window method

The original FVRS implemented ROI extraction using fixed window method. After raw FV image was captured, a predefined window of 264 x 88 was used to crop the ROI. This method is fast and easy to implement. However, there are a few disadvantages that cause this method to be unreliable. First, it requires users to place their fingers at the same position as enrolment during verification process. Second, ROI extracted might include unwanted information as it does not account for the misplacement of finger. This causes failure in verification because the enrolled and verifying images may differ a lot.

2.3.2 Inner contour method

In Leong's (2016) proposed method, ROI was extracted based on inner contour of finger edge. First, unnecessary background was removed by cropping. Then, the image was scaled down to 5 times smaller than origninal image to shorten the processing time. Canny edge operator was subsequently employed to determine the edge. Next, two vertical lines were drawn based on the inner contours of edges. The ROI was finally extracted as shown in Figure 2.1.

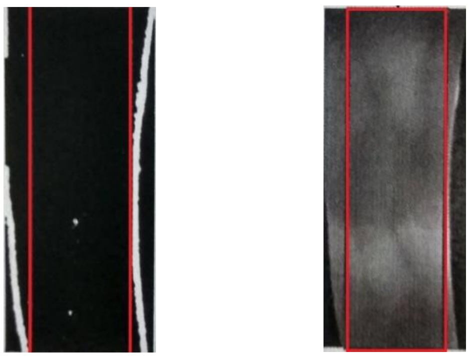


Figure 2.1: Inner Contour ROI Extraction (Leong 2016)

Leong's (2016) method has the same advantage as original FVRS. Besides that, it is also able to crop out only useful information using inner contour of finger edge. Nevertheless, the disadvantage outweigh the advantages of this method. This is because it may crop out inconsistent ROI with regard to finger placement, thus causing inconsistent FV information. For example, if one positions one's finger slanted to the left, the ROI extracted will contain less information due to lesser distance between inner contour.

2.3.3 Maximum row-sum value based on distal phalangeal joint

Yang & Shi (2012) proposed an ROI extraction by using distal interphalangeal joint localization. Figure 2.2 shows distal interphalangeal joint, which is the joint near fingertip. A predefined window was set to crop out uninformative background from the FV image. Then the pixel values at each row image were accumulated. The maximum row-sum was pinpointed to approximately denote the position of distal inter-phalangeal joint as shown in Figure 2.3(a). Lastly, a window was used to crop out the ROI where the maximum row-sum was 2/3 the height of ROI window as illustrated in Figure 2.3(b).

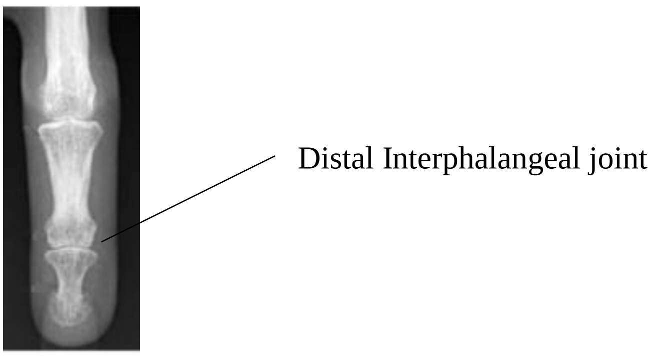


Figure 2.2: Distal Interphalangeal joint structure (Yang & Shi 2012)

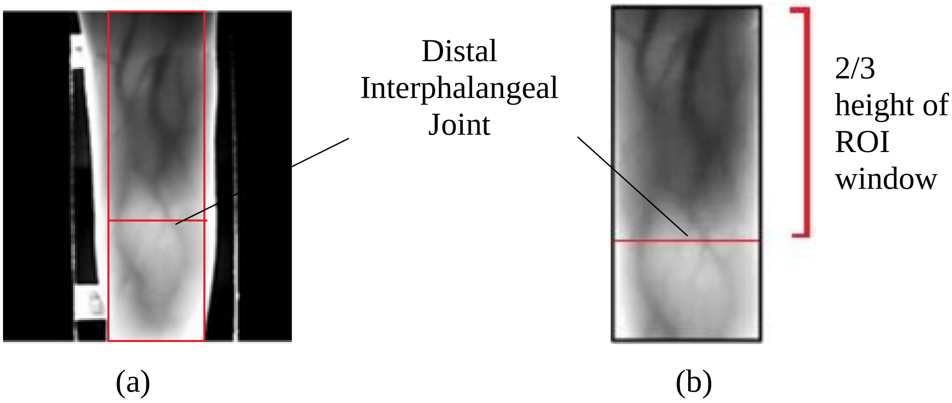


Figure 2.3: ROI localization. (a) Interphalangeal joint position;

(b) ROI obtained (Yang & Shi 2012)

This method is able to obtain localized ROI by estimating the position of distal phalangeal joint. However, it does not take into account the misalignment of finger position. There is a chance where the predefined window crops out part of informative data when users misplace their fingers, causing data loss. Furthermore, calculation of row-sum value is easily affected by illumination.

2.3.4 Single sliding window based on phalangeal joints

Yang et al. (2013) improved the aforementioned method by using a sliding window-based ROI extraction. First, they used a predefined window to crop out a candidate region from the original image acquired. Its purpose was to remove noises and useless information. Figure 2.4(a) and Figure 2.4(b) show the predefined window and cropped finger vein candidate region respectively. Then the edges of finger were detected by applying Sobel edge detector and subtract it from denoised binarized image. From the edges found, the midpoints of the finger edges were calculated for linear fitting straight line (red line) synthesis as shown in Figure 2.4(c). Since finger shape is irregular, (Yang et al. 2013) proposed that the FV image is considered skewed if only the difference value between maximum and minimum column is more than 15 pixels. Skew angle was computed and used to rotate image if the difference value is more than 15 pixels, or in other words the image is slanted as illustrated in Figure 2.4(c). The calculations are as follow:

(a) Equation of straight line synthesized by all midpoints is shown in Equation (2.1).

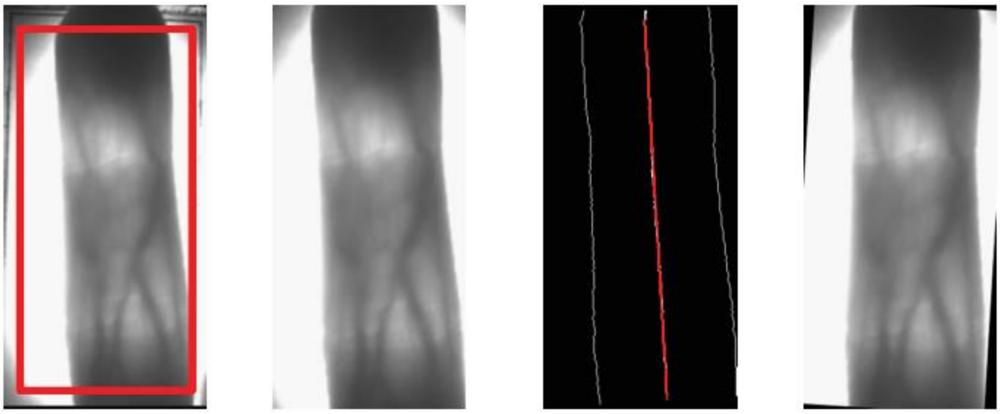
$$y = ax \tag{2.1}$$

where a denotes the slope coefficient of the straight line, y denotes the y-axis and x denotes the x-axis.

(b) Calculation of skew angle is shown in Equation (2.2).

$$\propto = \arctan(a) \times 360/2\pi \tag{2.2}$$

where $\propto$ is the skew angle and a is the slope coefficient of straight line obtained.



(a) (b) (c) (d)

Figure 2.4: Skew image detection and correction. (a) Predefined window in red; (b) Candidate region; (c) Finger edges; (d) Corrected FV image (Yang et al. 2013)

After correction of orientation, Yang et al. (2013) locate the distal inter-phalangeal joint and proximal inter-phalangeal joint as the localized benchmark for ROI extraction. Distal inter-phalangeal joint is the upper joint of our finger, which is near to the fingernail. Proximal inter-phalangeal joint is the lower joint of our finger. This is because phalangeal joint is composed cartilage, articular cavity filled with synovial fluid and synovium that have clearance to allow more NIR light to penetrate. As a result, phalangeal joints are generally brighter than other parts of FV image and have higher sum of gray value as shown in Figure 2.5. First, internal tangents of finger's edge were used to crop out unnecessary background image by using Sobel edge detector on binary finger edge image as shown in Figure 2.6. Then, the maximum sum of gray value was found using sliding window with 50 rows. The sliding window slid from top of FV image to bottom and calculated the sum of gray value with Equation (2.3):

$$S_p = \sum_{j=1}^{w} F(i,j) \; i = 1,2,\ldots,50 \tag{2.3}$$

Where S_p denotes the sliding window, w denotes the width of FV image key area, i and j represent row and column respectively.

Next, positions of two phalangeal joints were estimated based on maximum sum of gray values. Distal inter-phalangeal joint was searched from the top half of FV image, that was from the 1st window to the 205th window. A rule established by Yang et al. (2013) after careful observation was that distance between the two phalangeal joints is more than 100 rows. Therefore, proximal inter-phalangeal joint was searched from the 100th row after distal phalangeal joint position to the last window of the image. Besides that, they also found that phalangeal joints are usually located at the bottom of the window, so the position of phalangeal joint is the sum of the position of the window and 49 (sliding window has 50 rows). Equation (2.4) and Equation (2.5) show the computation of distal phalangeal joint and proximal phalangeal joint estimation respectively:

$$r_1 = \arg\max(S_p) + 49 \; p \epsilon [1, 205] \tag{2.4}$$

$$r_2 = \arg\max(S_p) + (r_1 + 100 - 1) + 49 \; p \epsilon [r_1 + 100, 411] \tag{2.5}$$

where r_1 denotes the position of the distal inter-phalangeal joint, r_2 denotes the position of the proximal inter-phalangeal joint, S_p is the sliding window.

The height and width of ROI were defined after two phalangeal joints locations were found. For height definition, Yang et al. (2013) calculated two distances, which are d_1 the distance between two phalangeal joints and d_2 the distance from proximal inter-