Extract an Effective Region of Interest using Automated Thresholding for Finger Vein Biometric

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***Abstract* - The development in the consumer's electronics demands for high security, accuracy and high speed of authentication. Human behavioral and physiological features in biometric have a large scope at providing solutions for security issues. Finger vein based personal authentication provides a better degree of security that protects information and control access much better. To explore the effective region from the acquired finger vein image, we proposed an identification of region of interest (ROI) based on automated thresholding. It is usually composed of finger region segmentation, image orientation correction, and ROI detection. In this paper we have used image pre-processing, batch processing and thresholding transformation concepts to extract meaningful ROI. The proposed automated thresholding to detect the ROI of the image has been studied, implemented and tested over the SDUMLA-HMT database.**

***Index Terms* - Edge detection, Histogram, Region of interest, Segmentation, Thresholding.**

I.INTRODUCTION

The recent evolution in digital technology and IOT (Internet of Things) demands for high security to maintain privacy for an accurate and higher speed of authentication. Biometrics (physiological or human behavioral features) can be used for the purpose of user identification and verification. In 1992, the idea of using finger vein patterns based personal authentication first came into existence, after that a lot of research has been done in this domain. Since 1997, Hitachi Ltd. Japan has been exploring the finger vein technology and became first to commercialize the finger vein authentication into product form which was released in 2002. In 2004 Hitachi developed ATM (Automated Teller Machine) applications and commercialized them in 2005.

Existing basic biometrics like passwords, tokens, access cards and personal identification numbers (PIN) are cheap and easy to implement but can be forgotten or stolen or exposed easily. Most popular biometric fingerprints are not permanent, they suffer from aging, skin disease, dirt, scars and duplicates can be created, palmprint can be easily frayed, signature can be easily copied or dubbed. Face recognition becomes difficult in the case of its occurrence such as wearing makeup glares, head wearing hats or caps. Iris identification proves most accurate and secured but very unfriendly/unacceptable due to the need for direct application of light into the eyes.

Whereas vascular pattern-based finger vein biometric not only provides a better degree of security that protects information and control access but also obeys all biometric characteristics like uniqueness, universality, user friendliness, permanence, acceptability, convenience, easy enrolment, difficult to spoofing. As every individual person has a unique and distinct finger vein, even the twins' finger vein pattern cannot be the same. Finger veins are hidden beneath the skin and not visible externally, so it does not leave any trace marks while enrolling and becomes very difficult to steal or forge. It also ensures liveliness as it can only be taken only from a live person. It has no aging effect so once acquired/collected/signed up does not require re enrolment.

In spite of all these merits/positive aspects, the key challenges in finger vein identification/authentication in practice are; first one is the quality of the finger vein images (as they are easily affected/ influenced due to some environmental conditions such as complicated background, uneven illumination, ambient temperature ,finger pressure) and another problem is the image distortion such as image translation, orientation, scale, scattering due to the variance of the finger structure, finger posture during /at the time of image capturing /acquisition .All these factors may contribute to inaccurate detection of regions of interest (ROI) and result in degrading the accuracy performance of the finger vein personal authentication.

One way to deal with the above problem is to improve the quality of image capturing /acquiring devices. Another way is to improve the feature extraction method to handle the lower quality image. Some feature extraction methods can detect the position of the vein effectively but cannot detect all the points of the vein which will result in losing some meaningful information.

II. RELATED WORK

Most of the investigations have focused on finger vein ROI extraction, finger vein image enhancement, and novel finger vein feature representation methods. Various research has been done and is still in progress related to the finger vein authentication system. A literature survey on finger vein is done which includes many IEEE, MDPI, Elsevier and many more papers is presented here:

Kono et al. [1] research department, medical systems of Hitachi Ltd, Japan proposed finger vein pattern matching as a novel approach for individuals' identification. Miura et.al.[2]and [3] have successfully investigated repeated line tracking and maximum curvature points feature extraction by calculating local maximum curvatures in cross-sectional profiles of a vein image with various widths and brightness of finger vein image. Ajay Kumar et al. [4] proposed automated finger image matching by fusion/utilizing both the finger vein surface and finger texture features simultaneously. Yanagawa et al. [5] described the diversity of finger vein images and its usefulness in personal dentification using 2024 finger vein images from 506 persons.

Wonseok Song et al. [6] experiments finger vein verification based on mean curvature by considering its geometric shape and finding the valley-like structures with negative mean curvatures. For extracting the features, they selected ROI which has a high possibility of being finger vein regions. In order to prevent the variation of the curvature caused by the varying thickness and brightness of the veins they applied gradient normalization. Experimental results show that while maintaining low complexity, the proposed method achieves 0.25% equal error rate, which is significantly lower. Yang et al. [7] and [8] used a sliding window-based method for determining region of interest and to enhance the finger-vein region in an image they used the circular Gabor filter. Shan Juan Xie et al. [9] have described a Guided Gabor filter which is to extract the finger vein pattern without any segmentation processing, and lower performance reduction for poor quality images. Qui et al. [10] proposed region growth-based feature extraction method for finger-vein recognition.

Yang et.al [11] highlighted the problem of vein feature extraction and its localization due to the presence of interphalangeal joints. They have proposed an effective method with use of a steerable filter for segmentation and feature extraction along with use of the nearest neighbor as a classifier Vlachos et.al. [12] makes use of Mumford Shah Model for the image enhancement, along with this it makes use of local entropy thresholding, morphological dilation and filtering with template matching as a classifier. Huang [13] has proposed a wide line detector and pattern normalization model based on fingers cross-section are approximately ellipses and the veins acquired are near the finger surface. The proposed model can correct the distortion caused by the poles more effectively. Liu, Li. [14] successfully implemented a wide line detector method which can obtain all the points of the lines for the palm print identification and also by applying a simple normalization method and conventional matching method they try to solve /avoid the effect of shifting and rotation in some directions but in other directions the problem still exists. Lu Yu et al. [15]. proposed an efficient and powerful local descriptor for finger vein recognition, known as histogram of competitive Gabor responses (HCGR) for segmentation and feature extraction. HCGR is based on a set of competitive Gabor response (CGR) which consists of two components: competitive Gabor magnitude (CGM) and competitive Gabor orientation (CGO). A set of CGR includes the information on magnitude and orientation of the maximum responses of the Gabor filter bank with a number of different orientations.

Perez Vega et al. [16] proposes the use of Sobel detector, enhancement filter and a binarization process at the pre-processing stage of image to get the vein pattern. It uses a personalized best bitmap (PBBM)for segmentation and marching as a classifier. Yang [17]-[19] highlighted the factors that cause degradation of quality of finger-vein images and proposed an effective scattering removal method to improve the visibility of finger-vein images for better interpretation. Also, discussed the venous region enhancement problem effectively and presented the use of Gabor filters as a solution for this problem. Finally, a Phase-Only-Correlation strategy is used to measure the similarity of the enhanced finger-vein images. Lu Yu et al. [20]. uses the Gabor filter, matched filter, repeated line tracking and maximum curvature method for feature extraction. They presented fingerprint and finger vein recognition on the basis of the score level. They also published an available database which was a part of a homologous multimodal database. Although there are some significant works in finger vein technology, there is always a scope for further research and improvement in this field. The stages of finger vein authentication systems can be broadly classified as image acquisition, pre-processing, feature extraction and finger vein matching based on the extracted features.

III. PROPOSED APPROACH

It is inevitable to present noise in the captured image due to the sensor quality, dust on camera and uneven light illumination, humidity, temperature, low contrast, image size and positional variation. In the image pre-processing several characteristics of the image are modified and making it convenient to identify key features for better interpretation of the viewer. In order to deal with the low quality of the finger vein images we require to remove the unwanted background from the finger vein images. We also need to decide which part of the image is most suitable for feature extraction. The acquired images are first subjected to several pre-processing techniques that includes: segmentation, identification of region of interest ROI, normalization of finger vein image, correction of positional variation/ alignment of finger (translation and orientation correction), and finally Image enhancement using histogram equalization to extract valuable features for matching.

A Segmentation: Segmentation of image makes the representation of digital image to extract useful information like pixels, boundaries, contours which is much more meaningful and easier to study. The acquired finger vein image has many unwanted non veinous regions beside the finger vein region resulting in the low accuracy rate of the finger vein authentication. To improve its accuracy, we first separate the undesirable region / background from the finger vein region. Various methods are existing for segmentation but according to our dataset thresholding is best fits. Thresholding is the simplest way to use image binarization which converts a grayscale image to a binary one Thresholding converts each pixel of image in two parts which is decided by threshold value T. If pixel intensity is greater than T then pixels convert to useful finger vein region and if less than T then they will lie in the background. The problem then is how to select the correct threshold. In many cases finding one threshold compatible with the entire image is very difficult and, in many cases, even impossible. Therefore, the automated threshold is needed where an optimal threshold value has determined the Centre of the object as the finger region. Thresholding is classified as histogram shape based, clustering based and entropy based, spatial and local. Figure1 shows the thresholding effect on finger vein image.

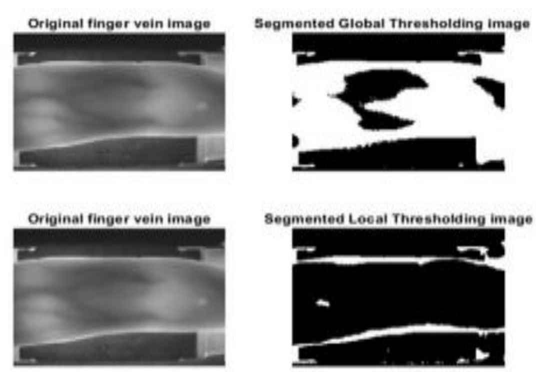

Fig1.Thresholding Transformation Finger vein image

B Region of interest extraction: Thus, to find a region of interest (ROI) we need to trim or crop the captured image so that information is taken mostly from the useful region of the finger vein images. Images obtained after cropping are now processed with edge detection, noise removal/denoising, sharpening, brightening of an image, contrast adjustment. The length of ROI is detected using phalangeal joints and width of ROI is calculated using the internal tangents of edges of fingers. Since the size of index middle and ring finger varies, after determining the ROI, the finger vein image has to be normalized/resized to accommodate the geometrical changes due to the posture variation and orientation of the finger. In order to correct skewed images caused by ROI variation, images should be resized to obtain the consistent size of images. Steps used to extract ROI from vein image are given in Algorithm 1. In addition, an example of ROI extraction is shown in Figure2.

Algorithm 1: -

1. Remove the border of the image.
2. Binarization of image using automated thresholding.
3. Boundaries are dilated by using morphological operations.
4. 8-neighborhood connectivity algorithm is applied to remove small sized connected components.
5. 5 Normalize image to 255.

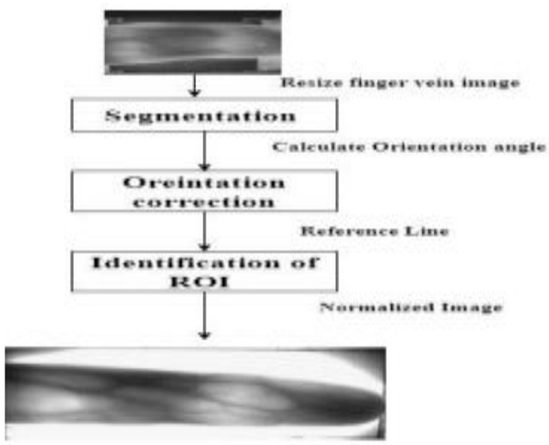

Fig 2. ROI of Finger vein image

C Normalization: After extracting the ROI The size of the ROI is different from image to image due to personal factors such as different finger size and changing location. Therefore, it is necessary to normalize/resize the original image to the same size before feature extraction. This can be done using the optimum scaling factor.

D Alignment of finger: The main problem we may encounter while capturing the images, there is a possibility that the user may tilt his/her finger a little to the right or left. To rectify/solve this problem, we have used various edge detection techniques to find the upper and lower finger edges. Figure3 shows that a canny edge detector is an optimal edge detection technique. It isolates noise from the image before finding edges of an image without affecting the meaningful /useful feature of the image.

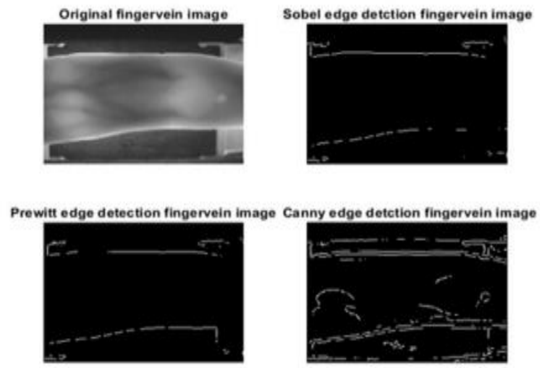

Fig 3. Edge Detection of Finger vein image

And also, on the basis of maximum and minimum abscissa values of the finger, the width and height of the finger region is obtained. After that we calculate orientation angle theta using least-squares estimation which is highly dependent on the accuracy of finger edges detection.

$$k = \sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) \Big/ \sum_{i=1}^{n}(x_i - \bar{x})^2$$

$$b = \bar{y} - k\bar{x}$$

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

$$\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \qquad \text{Where } x_i = 1, 2, \ldots, n, \; y_i = 1, 2, \ldots, n$$

$$\theta = \begin{cases} -\arctan(k), & k < 0 \\ \arctan(k) & k \geq 0 \end{cases}$$

E Image Enhancement: In order to reduce the complexity of the subsequent feature extraction process image enhancement plays an important role in performance accuracy of finger vein authentication. The quality of the acquired image can be enhanced by image contrast, brightness, sharpening, removing the noise content with the help of filters, using morphological operators and histogram equalization. We mainly focus on contrast enhancement. In our research work we have used histogram equalization method, which contributes to a higher accuracy for better matching performance with the previously enrolled /stored image in the database. Suppose we have an image which is predominantly dark, then its histogram would be skewed towards the lower end of the grayscale, and we need to stretch out the gray levels at the dark end to produce a more uniformly distributed histogram so that the image would become much clearer. Figure 4 shows the histogram of original and histogram of equalized finger vein image.

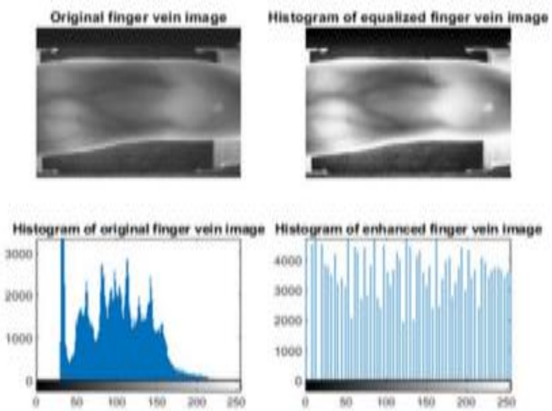

Fig 4. Histogram of finger vein image

IV. EXPERIMENT AND RESULT

Extensive experiments have been performed on the SDUMLA-HMT database of Shandong University, China. The device used to capture finger vein images is designed by Joint Lab for Intelligent Computing and Intelligent Systems of Wuhan University. This database consists of finger vein images captured from 106 volunteers, including 61 males and 45 females with age between 17 and 31. In the capturing process, each subject was asked to provide images of his/her index finger, middle finger and ring finger of both hands, and the collection for each of the 6 fingers is repeated for 6 times to obtain 6 finger vein images. The finger vein database is composed of 6×6×106=3,816 images. Every image is stored in "bmp" format with 320×240 pixels in size. The total size of the finger vein database is around 0.85G Bytes [22].

To process thousands of images with just a few clicks we have used a batch processing concept. We can specify a size or file type, and then a script runs to convert the images. And nearly every image processor comes with a unique feature set. Figure 5(a) shows uploading of 3816 finger vein images database and Figure5(b) shows simulated result of ROI process.

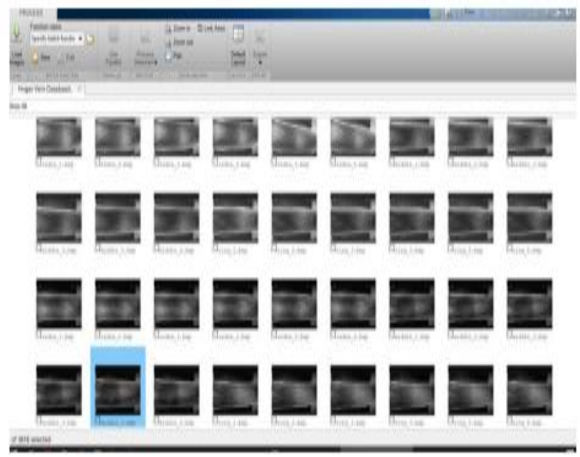

Fig 5(a). Loading of finger vein Database

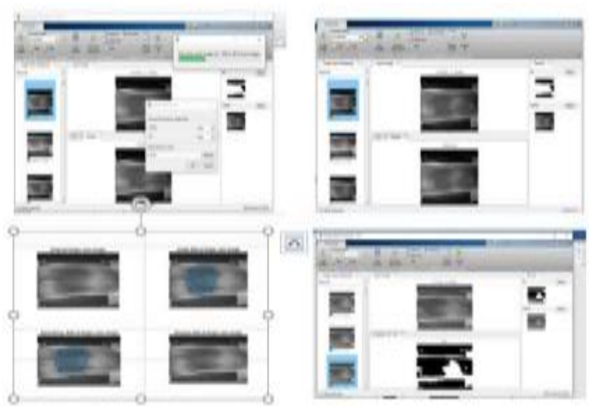

Fig 5(b). Simulated result of ROI Process

V. CONCLUSION

In this paper, we proposed a finger vein ROI method to eliminate image translation, orientation, scattering, complicated background, collection posture, and uneven illumination. We achieved these in three steps, which include segmentation, orientation correction, and ROI detection. We have used the least-squares method to estimate corrected orientation angle, which is highly dependent on the accuracy of finger edges detection. With this calculated angle we segmented false background from useful finger vein images in order to extract a useful feature we use automated thresholding techniques to detect a region of interest. Experimental results have illustrated that the proposed method is robust for the aforesaid influences.

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