A Biometric Authentication System using VPR Technology

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Abstract—**This paper presents a new approach to improve the performance of finger vein identification systems. Here proposed a method of personal identification based on finger vein patterns. An image of a finger captured under infrared light contains not only the vein pattern but also irregular shading produced by the various thickness of the finger bones and muscles. The proposed method extracts the finger vein pattern from the unclear image by using line tracking that starts from various positions. The previously proposed finger vein identification approaches illustrates it superiority over prior published efforts. The finger vein is a blood vassal network under the finger skin. The network pattern is distinct for each individual, unaffected by aging and it is internal i.e., inside human skiu which can always guarantee more security authentication. In this proposing study to an analysis of different techniques for Finger vein feature extraction. The basic and important principle, different feature extraction techniques and performance measuring are briefly analysed. Most of the existing work is functionally described and compared in three parts, i.e. Finger vein image acquisition, pre-processing and feature extraction.**

Keuwords-component; Personal identification - Biometrics - Finger vein - Feature extraction – Line tracking

I. INTRODUCTION

Personal identification technology is applied to a wide range of systems including area acess control, PC login, and e-commerce. Biometrics is the statistical measurement of human physiological or behavioral triats. Biometrics techniques for personal identification have been attracting recently because conventional means such as keys , passwords, and PIN numbers have problems in terms of theft, loss, and reliance on the user's memory.

In the area of biometric identification, security and convenience of the system are important [1]. In particular, the systems require high accuracy and fast response times. Biometrics methods include those based on the pattern of fingerprints [6-8], facial features [15], the iris [11], the voice [9], the hand geometry [7], or the veins on the back of the hand [9]. However, these methods do not necessarily ensure confidentiality because the features used in the methods are exposed outside the human body. These methods can therefore be susceptible to forgery.

To solve this problem, here proposed a biometric system using patterns of veins within a finger, that is, patterns inside the human body [2,3]. In this system, an infrared light is transmitted from the backside of the hand. A finger is placed between the infrared light source and camera. As hemoglobin in the blood absorbs the infrared light, the pattern of the veins in the palm side of the hand is captured as a patter of shadows.

The captured images contain not only vein patterns but also irregular shading and noise. The shading is produced by the varying thickness of finger bones and muscles. Therefore, regions in which the veins are not sharply visible exist in a single image.

To develop highly accurate personal identification systems, finger vein patterns should be extracted precisely from the captured images, and the process must be executed speedily in order to satisfy requirements for user convenience.

Conventional methods for extracting line shaped features from images include the matched filter method [4]. The matched filter and morphological methods can execute fast feature extraction because all that's required is to filter th image. However, this can also emphasize is to filter the image. However, this can also emphasize irregular shading, which presents an obstacle to personal identification since this obscures parts of patterns of veins. Moreover, dots of noise are also emphasized because continuity is not considered.

When the connection of emphasized edge lines is used to extract a finger vein pattern, line extraction can be executed if one takes into account continuity. However, the differential operation and optimization of the line connections carry immense computationally costs. It may take 10 or more minutes to process an image. Therefore, this method is not suitable when real-time processing is required.

WHY FINGER VEIN?

Compaed with other biometric triats, the finger vein has the following merits,

- The vein is hidden inside the bogy and is mostly invisible to human eyes, so it is difficult to forge or steal.
- The non-invasive and contactless capture of finger - vein ensures the convenience for the user, and is thus more acceptable.

- The finger-vein pattern can only be taken from a live body. Therefore, it is a natural and convincing proof that the subject whose finger-vein is successfully captured is alive.

Vein recognition technology is categorized into two types: one is hand vein recognition, and the other is finger vein recognition [8]. Both technology has their own merits, compared to the hand vein recognition, the equipment of finger vein recognition requires higher technological needs. The characteristics of finger-vein includes high protection, uniqueness, living body identification, internal characteristics, non-contacting, small sample file, a higher level of security and so on.

Finger Vein Identification steps are given as follows: Finger vein image acquisition, Pre-processing of image, Feature extraction, matching and verification.

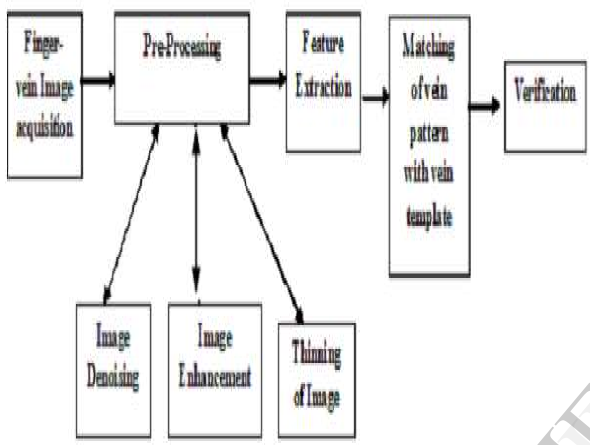

Fig.1. Functional Diagram of Finger-Vein Biometrics

A. *Finger Vein Image Acquisition*

A special imaging device is used to obtain the infrared image of the finger. An infrared light irradiates the backside of the hand and the light passes through the finger.

A camera located in the finger side of the hand captures this light. The intensity of light from the LED is adjusted according to the brightness of the image. As haemoglobin in the blod absorbs the infrared light, the pattern of veins in the finger are captured as shadows. Moreover, the transmittance of infrared light varies with the thickness of the finger. Since this varies from place to place, the infrared image contains irregular shading.

B. *Pre-Processing*

Image pre-process can be done for later analysis and use of an image. The role of pre-processing module is to prepare the image for feature extraction by enhancement, segmentation, filtering, thinning etc

C. *Image Denoising*

The Median filter is used for noise reduction. Removing noise from an image improves the results for the image later processing such as edge detection on an image.

D. *Image Enhancement*

The image enhancement is an essential step for higher image quality to get better matching performance. In this objective of enhancement is to process an image so that the result is more. The image given will be crop out and enhanced and filtering will be done. Filtering is to reduce the noise and filter out those unwanted object by using histogram technique where enhancing the image quality.

E. *Thinning*

Thinning is one types of morphological function. It is used to remove selected foreground pixels from a binary image. This function used to join up the output of edge detector by shrink all lines to a single pixel thickness. In this process have more accuracy for matching function.

F. *Feature Extraction*

During this process morphological is used with the structuring element small object from the image will be removed and morphological method or other equivalent method will be applied for further process of matching.

G. *Verification*

After the extracted image will be given to verification stage. In this stage the vein template image and input image should be compared. Then the matching original image is to be identified.

II. BLOCK DIAGRAM AND FINGER IMAGING

The block diagram of the proposed system is shown in fig.1. The fingers presented for the identification of subjects are simultaneously exposed to webcam and infrared camera as illustrated from the device of our imaging device in fig.2(a). The dorsal side of finger is exposed to the near infrared frontal surface illuminators, using light emitting diodes whose illuminators, using light emitting diodes whose illumination peaks at 850 nm wavelength, while the frontal surface entirely remains in the contactless position with both of the imaging cameras. Here the imaging system is unconstrained,i.e., it does not use any pegs or finger docking frame, it may not be designed as completely touchless. This is because the user often partially or fully touches the finger dorsal surface with the white diffusion background which holds the infrared illuminators beneath.

The finger vein and finger texture images are simultaneously acquired using the switching device/hardware that can switch the infrared illumination at a fast place. Fig. 2(b) shows a typical image samples acquired from our device from left index finger. The near infrared illumination incident on the finger dorsal surface is absorbed by the branches of arteries, veins and hemoglobin in the blood. However, the scattering and the absorption coefficients of bio-tissue is significantly different to that of blood for the infrared illumination [10]. The higher scattering coefficient results in more path changes of incident inferred illumination from the blood than those resulting from the surrounding tissues. Therefore, it is scattering from infrared illumination, rather than absorption, that dominates and results in darker appearance of finger vein patterns.

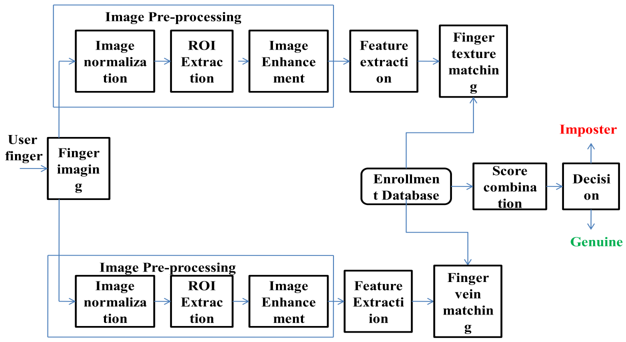

Fig.1. Block diagram for personal identification using simultaneous finger vein and finger texture imaging.

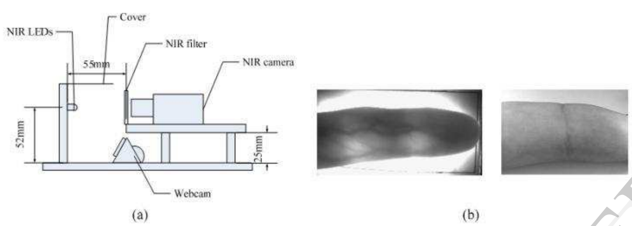

Fig.2. (a) Uncontrained finger identification using near infrared camera and webcam imaging. (b) simultaneously acquired image sample from the imaging device.

III. FINGER VEIN IMAGE PRE-PROCESSING

The acquired finger images are noisy with rotational and translational variations resulting from unconstrained imaging. Therefore the acquired finger images are firstly subjected to pre-processing steps (fig.3) that includes (i) segmentation of oregion of interest (ROI), (ii) translation and orientation alignment, followed by (iii) image enhancement to extract stable/reliable vascular patterns. Each of the acquired finger vein images is firstly subjected to binarization using a field threshold value as 230, to coarsely localize the finger shape in the images. Some portions of background still appear as connected to the bright finger regions, predominantly due to uneven illumination. The isolated and loosely connected regions in the binarized images are eliminated in two steps: firstly the sobel edge detector is applied to entire image and the resulting edge map is subtracted from the binarized image. Subsequently, the isolated blobs (if any) in the resulting images are eliminated from the area thresholding i.e., eliminating number of connected white pixels being less than a threshold. The resulting binary mask is used to segment region of interest from the original finger vein image. Fig.4. shows image samples from pre-processing steps that automatically ensures reliable segmentation of region of interest.

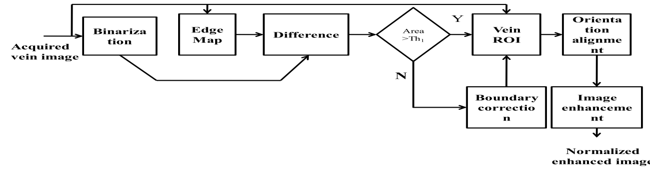

Fig.3. Block Diagram illustrating steps employed for the preprocessing of acquired finger vein images.

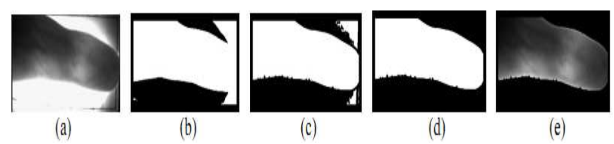

Fig.4. Extraction of roi from finger vein images. (a) acquired image sample. (b) binarized image. (c) edge map subtracted from (b). (d) ROI mask from image in (c). (d) ROI finger vein image.

A. *Image Enhancement*

The finger vein details in the acquired image, especially the thin ones, are not clear. This can be attributed to the uneven illumination and/or imperfect placement of fingers during the imaging. Therefore the vein images with low contrast and uneven illumination are subjected to nonlinear image enhancement. The acquired images are firstly divided into overlapping 30 × 30 pixels sub locks and average gray level in each of the blocks is computed. This average gray level in each of the blocks is computed. This average gray level is then used to construct average background image using bicubic interpolation. The segmentation finger vein images also include automatically filled background area that does not have any useful details and thus direct partitioning of image into sub blocks results in the biased estimation of background illumination. As shown in fig.4, the image enhancement has been quite successful in improving the contrast and details of acquired images.

IV. FINGER TEXTURE IMAGE PRE-PROCESSING

The acquired finger texture images from the webcam (640×480 pixels) are firstly automatically reduced to 580×380 pixels gray level images since the cropped part does not provide any useful details. This reduced size gray level image is employed for the pre-processing as shown in fig.5 and discussed in the following section.

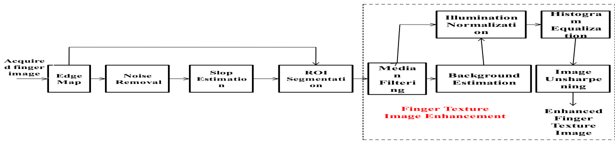

Fig.5. Block diagram illustrating key steps employed for the pre-processing of acquired finger texture images from webcam.

A. Gray Level Co-ocurrence Matrices

In statistical texture analysis, texture features are computed from the statistical distribution of observed combinations of intensitiers at specified positions relative to each other in the image. According to the number of intensity points (pixels) in each combination, statistics are classified into first-order, second-order and higher-order statistics.

The Gray Level Co-occurrence Matrices (GLCM) me thod is a way of extracting second order statistical texture features. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element $P(i,j\,|\,\Delta x,\Delta y)$ is the relative frequency with which two pixels, separated by a pixel distance $(\Delta x,\Delta y)$, occur within a given neighborhood, one with intensity i and the other with intensity j. The matrix element $p(i,j\,|\,d,\theta)$ contains the second order statistical probability values for changes between gray levels i and j at a particular angle (θ).

For an $M\times N$ neighborhood of an input image containing G gray levels from 0 to $G-1$, let $f(m,n)$ be the intensity at sample m, line n of the neighborhood.
Then

$$P(i,j\,|\,\Delta x,\Delta y)=WQ(i,j\,|\,\Delta x,\Delta y) \qquad (1)$$

Where

$$W=\frac{1}{(M-\Delta x)(N-\Delta y)}$$

$$Q(i,j\,|\,\Delta x,\Delta y)=\sum_{n=1}^{N-\Delta y}\sum_{m=1}^{M-\Delta z}A$$

and

$$A=\begin{cases}1, if\,(m.n)=i and f\,(m+\Delta x,n+\Delta y)=j\\ o, elsewhere\end{cases}$$

B. Texture Features from GLCM

A number of texture features may be extracted from the GLCM. Here the following notation are used.

G is the number of gray levels used.

μ is the mean value of P.

μ_x,μ_y,σ_x and σ_y are the means and standard deviations of P_x and P_y. $P_x(i)$ is the i th entry in the marginal-probability matrix obtained by summing the rows of $P(i,j)$:

$$P_x(i)=\sum_{j=0}^{G-1}P(i,j)$$

$$P_y(y)=\sum_{i=0}^{G-1}P(i,j)$$

$$\mu_x=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}P(i,j)=\sum iP_x(i)$$

$$\mu y=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}jP(i,j)=\sum_{j=0}^{G-1}(P_x(i)-\mu_x(i))^2$$

$$\sigma_x^2=\sum_{i=0}^{G-1}(i-\mu_x)^2\sum_{j=0}^{G-1}P(i,j)=\sum_{i=0}^{G-1}(P_x(i)-\mu_x(i))^2$$

$$\sigma_y^2=\sum_{j=0}^{G-1}(j-\mu_y)^2\sum_{i=0}^{G-1}P(i,j)=\sum_{j=0}^{G-1}(P_y(j)-\mu_y(j))^2$$

and

$$P_{x+y}(k)=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}p(i,j)\quad i+j=k \qquad (2)$$

for k=0,1,…..,2(G-1).

$$P_{x-y}(k)=\sum_{i-0}^{G-1}\sum_{j=0}^{G-1}P(i,j)\ \left|i-j\right|=k \qquad (3)$$

for k=0,1,….,G-1.

The following features are used:

- Entropy

$$\text{ENTROPY}=\ -\sum_{i=0}^{G-1}\sum_{J=0}^{G-1}p(i,j)\times\log(P(i,j)) \quad (4)$$

Inhomogeneous scenes have low first order entropy, while a homogenous scene has a high entropy.

- Sum of Squares, Variance:

$$\text{VARIANCE}=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(I-\mu)^{2}\,P(i,j) \qquad (5)$$

This feature puts relatively high weights on the element that differ from the average value of $P(i,j)$

V. EXPERIMENT AND RESULT

A. Experiment and image acquisition

In the experiment, infrared finger vein images captured from fingers, 6 images for one finger. The experiment procedure includes the following four steps: infrared finger vein image acquisition, image preprocess, vein feature extraction and matching.

Step 1: The schematic diagram obtained from near-infrared finger vein image is decribed in figure 2 (a) and (b).Using an array of mold type near-infrared LEDs(wavelength 850 nm) as the light source, its intensity of light can be manually adjusted. The dorsal side of the finger is illuminated by the LED array, and a CMOS camera with a infrared filter capture the image.

Step 2: Pre-process includes low-pass filter, finger edge detection, finger body extraction, finger rotation and size normalization. The figure 6 shows the flowchart of finger image preprocessing.

A 5*5 Gaussian low-pass filter is adopted to remove speckling noises in the original image. Sobel edge detection extracts the finger's outline, which describes the shape of the finger and can be used to extract the finger body. The areas outside finger is zero padded. Use least-squares line-fit of finger outline to estimate the slope angle of the finger. Then the finger image is rotated clockwise to be horizontal by the angle of the slope. At last, the finger image is cut off from the tip to the body by the normalized size.

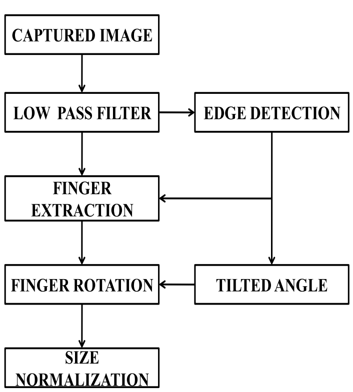

Fig. 6. Flowchart of the image preprocess

Step 3: To solve the brightness fluctuations and low contrast problems in the near-infrared finger vein image, we use the repeated line tracking to extract the vein feature[7]. This scheme consists of tracking a dark line, iteratively tracking the lines and obtaining finger vein patterns based on the number of times of tracking.

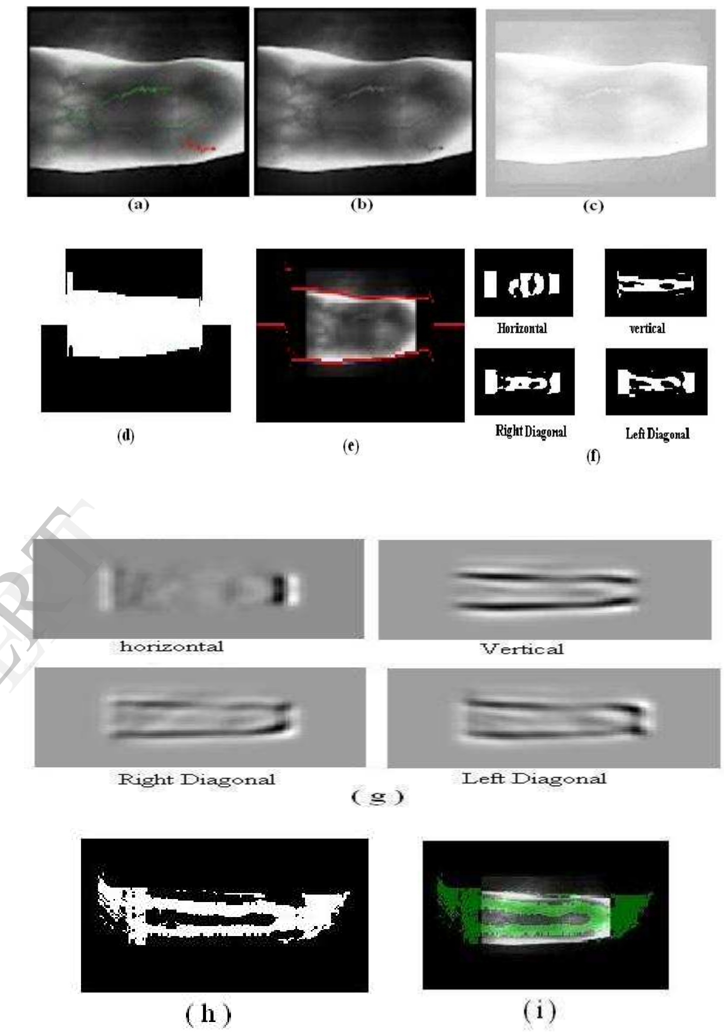

Fig.7. (a)Input image, (b)Preprocessing, (c)Histogram Equalisation, (d)Finger Region, (e)Finger Edge Image, (f)Curvature, (g)2nd order derivative, (h)Binarised veins, (i)Enhanced veins

B. Performance from Finger Vein and Finger Texture Combination

The experimental results presented in this section are focused to ascertain the performance improvement that can be achieved from the simultaneous acquisition of finger vein and finger texture images. The approaches that achieve the best performance in the last two sections were employed for score level combination. Figure 8 (a) shows the distribution of finger vein and finger texture matching scores from the genuine and imposter matches. The similar distribution of finger vein and finger texture matching scores but from 156 subjects is shown in figure 8(b). This figure illustrates promising separation of genuine and imposter matches, even from the index-to-middle finger vein and texture matching, and the combination of two scores can be explored for the performance improvement.

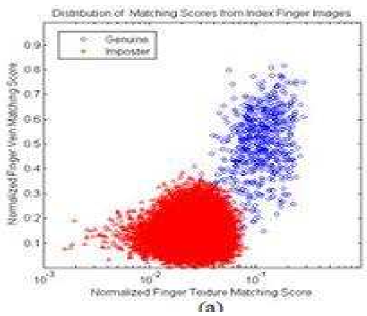

Fig.8. Distribution of finger vein and finger texture matching scores from index finger.

C. Dataset

To the best of my knowledge, no public finger-vein image database has yet been introduced. Therefore, we constructed a finger-vein image database for evaluation, which contains finger-vein images from a variety of ethnic/racial ancestries. Fig. 9 shows some example finger-vein images (after preprocessing) from different fingers.

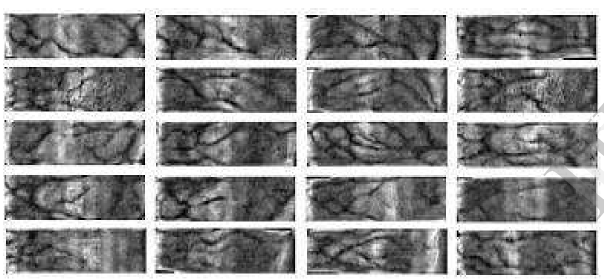

Fig.9. Finger-vein images from different fingers after preprocessing

VI. CONCLUSION

The present study proposed an end-to-end finger-vein recognition system based on the blanket dimension and lacunarity implemented on a DSP platform. The proposed system includes a device for capturing finger-vein images, a method for ROI segmentation, and a novel method combining blanket dimension features and lacunarity features for recognition. The images from 600 fingers in the dataset were taken over long time interval (i.e., from summer to winter) by a prototype device we built. The experimental results showed that the EER of our method was 0.07%, significantly lower than those of other existing methods. Our system is suitable for application in mobile devices because of its relatively low computational complexity and low power consumption.

Several new methods for detecting image edges in the presence of noise. In both spatial and scale-space approaches a priori information about the geometrical characteristics of edges was used to distinguish edges more accurately from noise. Probability factors are assigned to each pixel based on its chance of being on an edge. Both natural and computer generated images were examined to show the general applicability of the technique. It was shown that spatial and wavelet based techniques have different advantages and disadvantages. The spatial domain ap-proach is more successful in detecting and localizing the weak edges but can

produce false edges in response to noise. Although our wavelet-based edge detector is less sensitive to noise in-duced edges, it is not as accurate as the spatial domain method in localizing the edges.

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