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ENHANCEMENT OF SECURITY USING FINGER VEIN RECOGNITION

M.SOUNDARYA[1],J.ROHINI[2], V.PAVITHRA [3], V.RAMYA[4], S.NITHYA[5],
[1,2,3,4]IV Year Students, Dept of ECE, KPR INSTITUTE OF ENGINEERING & TECHNOLOGY, COIMBATORE.
[5] ASSISTANT PROFESSOR OF ECE

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ABSTRACT
The development of technology have increased the consumer electronics and mobile devices but is now challenging the protection of personal and private information from misuses owing to theft or loss. Biometrics, the intelligent security systems has the potential to become an irreplaceable part of many identification systems. However almost all previously available biometric systems have problem in management of time, space or both. Thus it cannot be used for mobile devices. Finger vein is non imitable biometric authentication scheme, that is based on biometrically generated key pairs. Finger vein recognition matches vascular pattern in an individual's finger to previously obtained data. The proposed system uses only 0.8 seconds to verify one input finger vein sample and equal error rate is about 0.07% on a database of 100 subjects, demonstrating that the design approach can be effective than other biometric system.
Key words: Biometrics, finger vein, mobile device, security system

INTRODUCTION

The society which we are living today is being electronically connected to form one big global village. Hence, it is important to recognize reliable person automatically conventional method of protecting private information is by using password or personal identification number(PIN) which are easy to implement but has the risk of exposure and being forgotten. Recognizing people from their body part yet from a powerful identification tool. This form of biometrics, which refers to automatic recognition of people based on their distinctive anatomical characteristics induces a variety of methods like face, iris, finger print, palm print, hand, shape, voice, signature and grait. But each of the above have their own disadvantages. For instance, finger print and palm print are usually frayed; voice, signature hands and iris are easily forged; face recognition is made difficult by face lifts or occlusion[1]. Hence we go for vein biometrics, where the network of blood vessels under a person's skin are used for identification. However it is also proven that the vein are unique to each finger and each individual and are said to be stable for much longer period of time[2].

Finger vein based recognition system holds below mentioned merits.

1) Liveness: Finger vein pattern can only be taken from a live body. Hence the subject whose vein is captured will be alive.

2) Immunity to forge or steal: vein is hidden inside body and is invisible to human eyes. Hence duplication is impossible.
3) User convenience: finger vein can be captured invasively without any unpleasant sensations and contagion

In addition, the quality of the captured vein pattern is not easily influenced by skin conditions as compared with palm vein based verification system, the size of the device can be made much smaller.

In this paper, we used a DSP based embedded platform to implement finger vein recognition in a reliable way and to reduce computational cost. The rest of the paper is organized as follows. The synopsis of the predictable scheme is given in piece 2. Section 3 explain the device for finger vein image acquisition. The recognition method is section 5. To conclude, explanation and remarks are given in section 6.

I. SYSTEM OVERVIEW

The overall procedure for the finger vein recognition system can be elaborated by explaining about 3 hardware module: image acquisition module; DSP main board and human machine communication module. Image acquisition module is to obtain the infrared image of the finger. The DSP main broad executes finger vein recognition algorithm, normalization, extraction, enhancement, feature extraction and matching. Human machine communication module is to establish a communication with the end user, display recognition result and receive input from users.

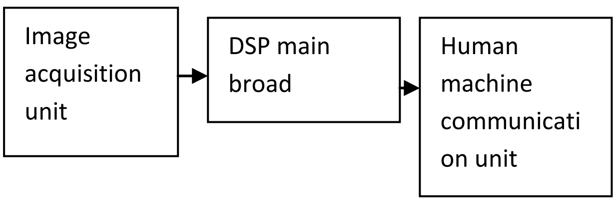


Fig 1: hardware diagram of proposed system

The proposed finger vein recognition algorithm consist of 2 stages: authentication stages and identification stages. Initially, obtained image is normalized then the region of interest(ROI) is detected. Image segmentation, alignment and enhancement is also done. For authentication stage, after preprocessing and feature extraction step, finger vein template database is built. In identification stage, input finger vein image is matched with corresponding template after extraction.

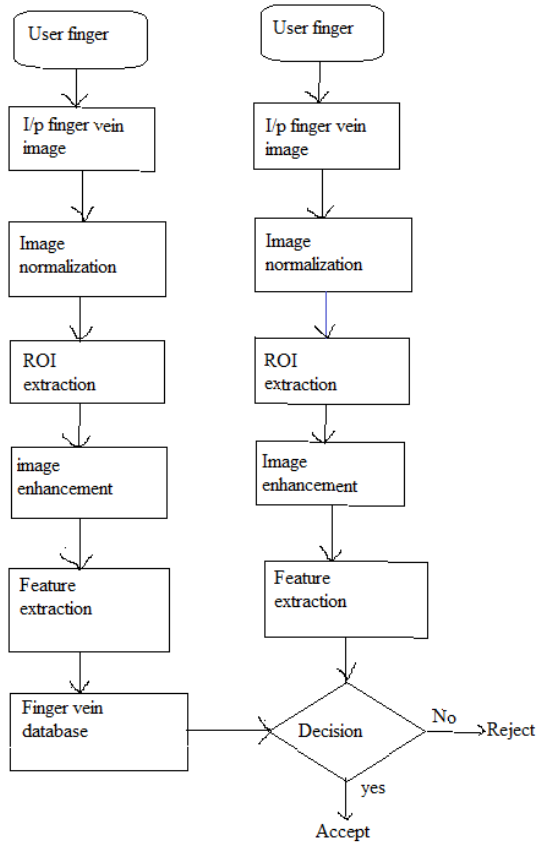


Fig 2 shown the flow chart of proposed recognition algorithm.

In this paper, a novel method based on fractal theory is introduced in section 4 in detail. This method is used because of its efficiency, less complexity and practicability.

II. FINGER VEIN IMAGE ACQUISITION

Finger veins lie below epidermis. As they are internal, visible lights cannot image them. Hence near infrared light (NIR) are used in vein imaging. It is because they can penetrate relatively deep into the skin as well as radiation of light can be absorbed greatly by deoxy hemoglobin [3].usually, finger vein patterns are imaged based on the principle of light reflection or light transmission[4]. We have used NIR imaging technique rather than far infrared(FIR) because of its use in multiple cases according to [5]. Our device mainly include NIR LD(near infrared laser diode) which is commonly used in fiber optic telecommunication, because of low attenuation losses in sio2 glass medium. A transparent acryl sheet of thickness 5mm is kept on the finger vein module to avoid uneven illumination of light. As

LEDs casts the shadow of the finger vein. We used laser diodes in our work. 580 x 600 pixel resolution, monochromatic camera is also used. A prototype of imaging device. Fig 2 (b, c, d, e) shows an example raw finger-vein images captured by our device.

III. RECOGNITION METHOD

A. Image normalization

As location and angle of the finger in the image vary each time, some form of normalization is always required. Articular cartilage, which is in the finger joint can be easily penetrated by NIR light. The image of the joint is brighter than that of other parts when irradiated by uniform NIR light. Hence in the horizontal projection of finger vein image, peaks of projection curve correspond to approximate position of the joints a in fig 4. As second joint of finger is thicker than the first joint, peak value at the second joint is less prominent. Thus the position of finger is determined using position of first joint.

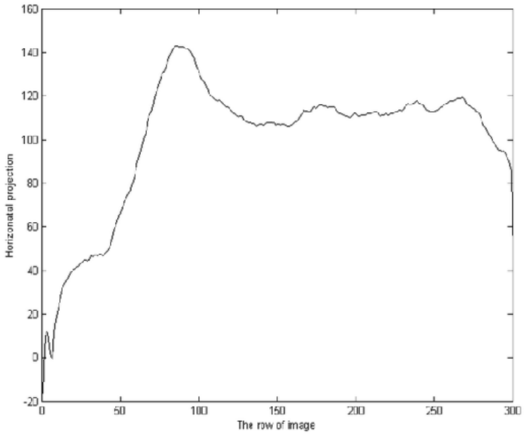


Fig 4: horizontal projection of the raw image

The alignment module includes the following steps. First, the part between the two joints in the finger-vein image is segmented based on the peak values of the horizontal projection of the image. Second, a Canny operator with locally adaptive threshold is used to get the single pixel edge of the finger. Third, the midpoints of finger edge are determined by edge tracing so that the id line can be obtained. Fourth, the image is rotated toad just the midline of the finger horizontally. Finally, the ROI of the finger-vein image is segmented according to the midline (see Fig. 6).

B. Image Enhancement

The segmented finger-vein image is then enhanced to improve its contrast as shown in Fig. 7. The image is resized to 1/4 of the original size, and enlarged back to its original size. Next, the image is resized to 1/3 of the original size for recognition. Bicubic interpolation is used in this resizing procedure. Finally, histogram equalization is used for enhancing the gray level contrast of the image.

C. Feature Extraction

The fractal model developed by Mandelbrot [10] provides an excellent method for representing the ruggedness of natural surfaces and it has served as a successful image analysis tool for image compression and classification. Since different fractal sets with obviously different textures may share the same fractal dimension [11], the concept of lacunarity is used to discriminate among textures. The basic idea of lacunarity in many definitions is to quantify the "gaps or lacunae" presented in a given surface,

which is used to quantify the deneness of a surface image. In this study, we focus on combining fractal and lacunarity measures for improving finger-vein recognition.

Let $f = g(i, j)$, $i = 0,1,\ldots,k$, $j = 0,1,\ldots,l$, where f denotes an image with k x l pixels, and $g(i, j)$means the gray level value at the (i, j)pixel. The gray level surface of $g(i, j)$can be viewed as a fractal [12]. First, for $g(i, j)$,u_0(i, j) = b_0 (i, j) = g(i, j).Second, for =1,2,3,....., the blanket surface is defined as follows:

$u_\varepsilon(i,j)=\max\{u_{-1}(i,j)+1,\max_{|(m,n)-(i,j)|\le} u_{-1}(m,n)\}$

$b_\varepsilon(i,j)=\min\{b_{-1}(i,j)+1,\max_{|(m,n)-(i,j)|\le} b_{-1}(m, n)\}$

which ensures that the upper surface $u_\varepsilon$is above $u_{\varepsilon-1}$ andalso at a distance of at least 1 from $u_{\varepsilon-1}$ in the verticaldirection. The profile of $u_\varepsilon$and $b_\varepsilon$do not change when εincreases to ε_n. The volume of the blanket $v_\varepsilon$can be computed by

$$v_\varepsilon = \sum_{i,j}(u_\varepsilon(i, j) - b_\varepsilon(i, j)) \qquad (2)$$

The surface area $a_\varepsilon$measured with the radius εcalculated by

$$a_\varepsilon = (v_\varepsilon - v_{\varepsilon-1}) / 2 \qquad (3)$$

Let a (ε)be the surface area of the blanket. Considering the Minkowski dimension [13], if $\varepsilon$is sufficiently small, we have

$$a(\varepsilon) = F\varepsilon^{2-D} \qquad (4)$$

where F is a constant, and D stands for the fractal dimension (FD) of the image. Two values of , i.e.ε_1 and ε_2,are used to compute FD, then we can get$a_{\varepsilon1} \approx F\varepsilon_1^{2-D}$ and $a_{\varepsilon2} \approx F\varepsilon_2^{2-D}$

Thus, we can deduce

, and take the logarithm at both sides to yield:

$$D \approx 2 - \frac{\log_2 a_{\varepsilon1} - \log_2 a_{\varepsilon2}}{\log_2 \varepsilon_1 - \log_2 \varepsilon_2} \qquad (5)$$

Peleg [14] discussed the factors affecting shrinking rate. When high gray level stands for white, the min operator of (1) will shrink the light regions corresponding to the particles, and the rate of this shrinking will only depend on the shape properties of the high gray level object. The max operator of (1), however, will shrink the background regions, and the rate of this shrinking will mainly be affected by the distribution of the high gray level object. In the case of finger-vein images, due to the directionality of the finger-vein, blanket growth can be made by directional maximizing (or minimizing) in the asymmetrical neighborhood instead of the symmetrical circular neighborhood. Considering the shape of the finger vein pattern, we modified (1) as follows, which can improve the rate of the shrinking and reveal the directional characteristics of the finger vein pattern.

u_{ε}(i,j)=max{$u_{\varepsilon-1}$(i,j)+1$\max_{|(m,n)-(i,j)|\leq 1}\{u_{\varepsilon-1}($m,n),$u_{\varepsilon-1}$(i-2,j)}}

b_{ε}(i,j)=min{$b_{\varepsilon-1}$(i,j)+1,$\min_{|(m,n)-(i,j)|\leq 1}\{u_{\varepsilon-1}($m,n),$u_{\varepsilon-1}$(i-2,j)}}

D. Lacunarity Based on Blanket Technique

Lacunarity is another concept introduced by Mandelbrot to quantify the gaps in texture images. It is a measure for spatial heterogeneity. Visually different images sometimes may have similar values for their fractal dimensions. Lacunarity estimation can help distinguish such images. Lacunarity can be defined quantitatively as the mean-square deviation of the fluctuations of mass distribution function divided by its square mean. It is also defined as the width of the mass distribution function of a set of points, given the ''box size'' [15]. Thus, a higher value of lacunarity implies more heterogeneity, as it means a wider mass distribution function, or a larger number of different mass values, of the set of points [16]. A lacunarity value is assigned for the center pixel of the image window, and the lacunarity value of each pixel in an image can be obtained by moving the *W* x *W* window throughout the whole image.

In our method, lacunarity is computed based on the blanket method [17]. The image $d_{\varepsilon}(i, j)$ is obtained according to $d_{\varepsilon}(i, j) = u_{\varepsilon}(i, j) = b_{\varepsilon}(i, j)$ (7)

Let $p(gv)$ be the probability of the intensity points whose gray values are gv on the surface of d_{ε}. The first and second moments of this distribution are then determined as

$$M^1 = \sum_{i,j} d_{\varepsilon}(i,j)\, p(d_{\varepsilon}(i,j)) \quad (8)$$

$$M^2 = \sum_{i,j} (d_{\varepsilon}(i.j))^2\, p(d_{\varepsilon}(i,j))$$

Thus, lacunarity can be computed by

$$\Lambda_{\varepsilon} = \frac{M^2-(M^1)^2}{(M^1)^2} \quad (9)$$

E. Matching

The blanket dimension distance *HD* between two finger vein patterns and the lacunarity distance $H\Lambda$ are defined as

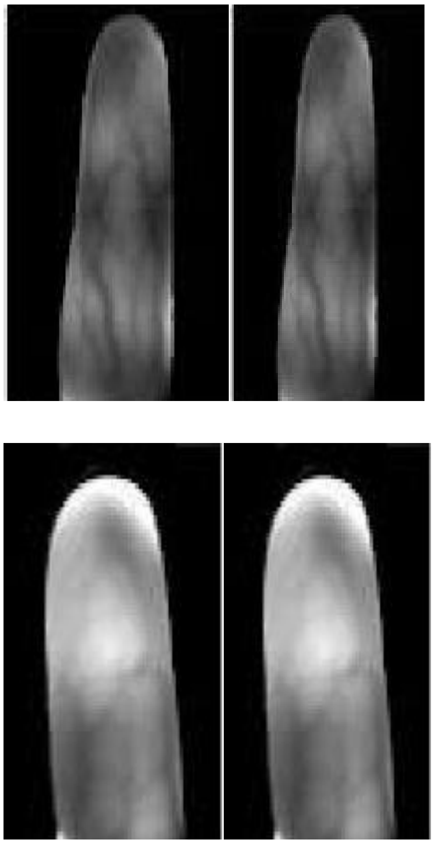
$$HD = \sum_{\varepsilon=2}^{4} \sum_{i,j} |D_{1\varepsilon}(i,j) D_{2\varepsilon}(i,j)| \quad (10)$$

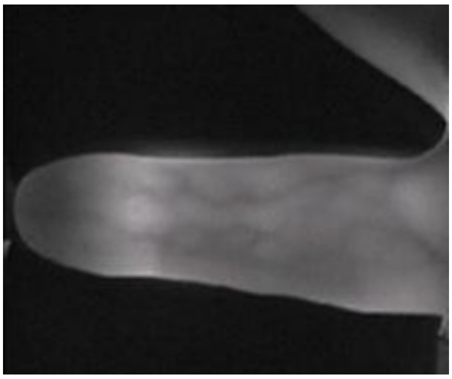
$$H\Lambda = \sum_{\varepsilon=2}^{4} \sum_{i,j} |\Lambda_{1\varepsilon}(i,j) \Lambda_{2\varepsilon}(i,j) \quad (11)$$

In our method, the dimension and lacunarity features are combined for finger-vein recognition: if $HD < th1$ and $H\Lambda < th2$ ($th1$ and $th2$ are thresholds), then the two finger vein patterns are considered to be from the same finger; if $HD > th1$ or $H\Lambda > th2$, they are considered to be from different fingers.

IV. EXPERIMENTAL RESULT AND PERFORMANCE EVALUATION:

Finger vein images from different fingers is shown in fig 6





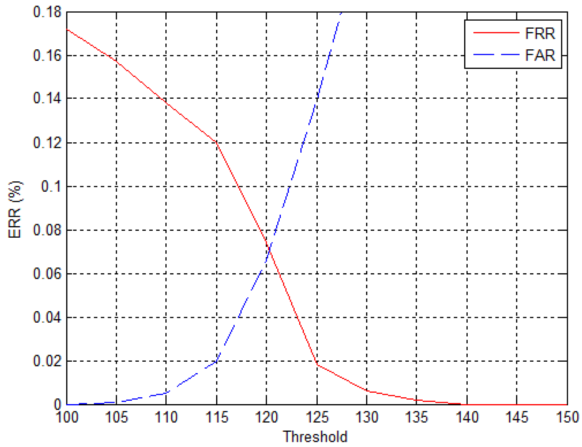


Fig 6 The FAR and FRR curves of the method combining the blanket dimension and lacunarity.

In biometrics, the performance of a system is evaluated by EER (equal error rate). The EER is the error rate when the FRR(false rejection rate) equal FAR (false acceptance rate) and is therefore suitable for measuring overall performance of biometric system because the FRR and FAR are treated equally. The curves of FRR and FAR are used to evaluate the performance of our proposed method. Fig 7 shows the FAR and FFR curves of the method combining both blanket dimension and lacunarity.

Table 1: comparison of parameters of different biometric technologies.

Biometric	universality	Uniqueness	permanence	collectability	performance	acceptability	Circumvention
face	high	low	med	high	Low	high	Low
Finger print	med	high	high	med	High	med	high
Hand	med	med	med	high	Med	med	med
Iris	high	high	high	med	High	low	High
Signature	low	low	low	high	Low	high	low
vein	high	med	Med	med	High	med	low

V. CONCLUSION

In this paper, we proposed a system that includes a capturing device for obtaining finger vein images, ROI segmentation method, novel method combining blanket dimension feature and lacunarity features for recognition. The experiment result showed that the EER of our method was 0.07%, significantly lower than those other existing methods. Because of its low computational complexity and low power consumption, our system is suitable for application in mobile devices and consumer electronics.

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