Finger Vein Extraction and Authentication Based on Gradient Feature Selection Algorithm

Parthiban, K, Amitabh Wahi, Sundaramurthy, S, Palanisamy, C
Department of Information Technology
Bannari Amman Institute of Technology
Sathyamangalam-638401
Tamilnadu, India
{Parthibank.se12, awahi, sundaramurthys, cpalanisamy}@bitsathy.ac.in

ABSTRACT: *In present days, Authentication by means of biometrics systems is used for personal verifications. In spite of having existing technology in biometrics such as recognizing the fingerprints, voice/face recognition etc., the vein patterns can be used for the personal identification. Finger vein is a promising biometric pattern for personal identification and authentication in terms of its security and convenience. Finger vein has gained much attention among researchers to combine accuracy, universality and cost efficiency. We propose 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 thicknesses of the finger bones and muscles. The proposed method extracts the finger-vein pattern from the unclear image by using gradient feature extraction algorithm and the template matching by Euclidean distance algorithm. The better vein pattern algorithm has to be introduced to achieve the better Equal Error Rate (EER) of 0.05% comparing to the existing vein pattern recognition algorithms.*

Keywords: Equal Error Rate (EER), Personal Identification Numbers (PINs), False Rejection Rate (FRR), False Acceptance Rate (FAR)

Received: 12 November 2013, Revised 17 December 2013, Accepted 23 December 2013

1. Introduction

The rise in the volume of digital data, as well as rapid developments in information technology, has seen information security become more important, requiring increasingly higher levels of data protection. Conventional security systems are constructed so as to allow authorized persons access to certain information sources, while preventing access by unauthorized persons. Biometric procedures for identifying personalities are attracting attention because conservative techniques such as keys, passwords, and PIN numbers carry the risks of being stolen, lost, or forgotten. There has been considerable research in biometrics over the last two decades. The list of physiological and behavioral biometric characteristics that has to date been developed and implemented is long and includes the face, iris, fingerprint, palm print, hand shape, voice, signature, and gait. Notwithstanding this great and increasing variety of biometrics, no biometric has yet been developed that is perfectly reliable or secure. For example, fingerprints and palm prints are usually frayed; voice, signatures, hand shapes, and iris images are easily forged; face recognition can be made difficult by occlusions or face-lifts; and biometrics such as fingerprints, iris and face recognition are susceptible to spoofing attacks, i.e., the biometric identifiers can be copied and used to create artifacts that can deceive many currently available biometric devices. The great challenge to biometrics is thus to improve recognition performance and be maximally resistant to deceptive practices. To this end, many researchers have sought to improve reliability and frustrate spoofs by developing biometrics that are highly individuating; yet at the same time, highly effective and robust. Finger vein pattern is just a promising qualified candidate for biometric-based personal identification.

The rest of this paper is organized as follows. An overview of the system which proposed here is in Section 2. Our recognition method is addressed in Section 3. Experimental outcomes are discussed in Section 4. Finally, conclusion and future enhancement of the algorithm is described in Section 5.

2. Overview of the System

The proposed finger-vein recognition algorithm contains two stages: the enrollment stage and the validation stage. Both stages start with finger-vein image preprocessing, which contain detection of the region of interest (ROI), image segmentation, align the scanned image, and enhancement. For the enrollment phase, after the preprocessing and the Gradient extraction stage, the finger-vein template recorded into database is built.

For the verification stage, the finger-vein image is inputted for matched with the corresponding template after its features are extracted. Figure 2 show the flow chart of the suggested algorithm. The proposed algorithm depicts several stages such as Image acquisition; Image preprocessing, vein extraction and template matching. The vein Extraction stage implements the Gradient feature selection algorithm [9] as discussed in next section. Some altered methods may have been proposed for finger-

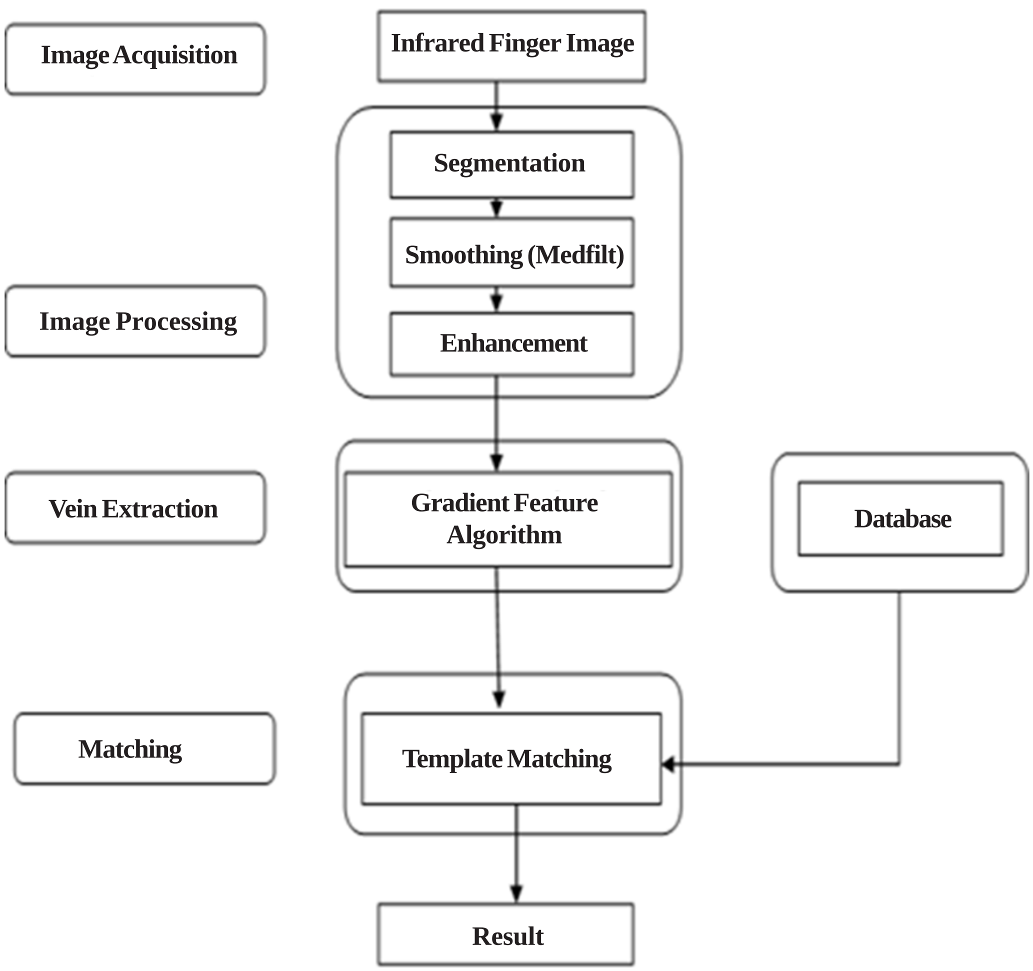

Figure 1. The Flowchart of the Proposed Recognition Algorithm

vein identical. In view of the computation complexity, competence, and feasibility, however, we propose a novel method based on the Gradient theory, which will be discussed in Section 3 in detail.

3. Proposed Algorithm

3.1 Image Preprocessing

The Captured finger vein image can contain various noise and distortion on it. To extract the feature vein patterns, the image captured have to be normalized by means of image preprocessing techniques. The resultant image is the high contrast image which is to be further processed for the extraction of vein patterns by the algorithm proposed. The procedure for preprocessing the image as follows:

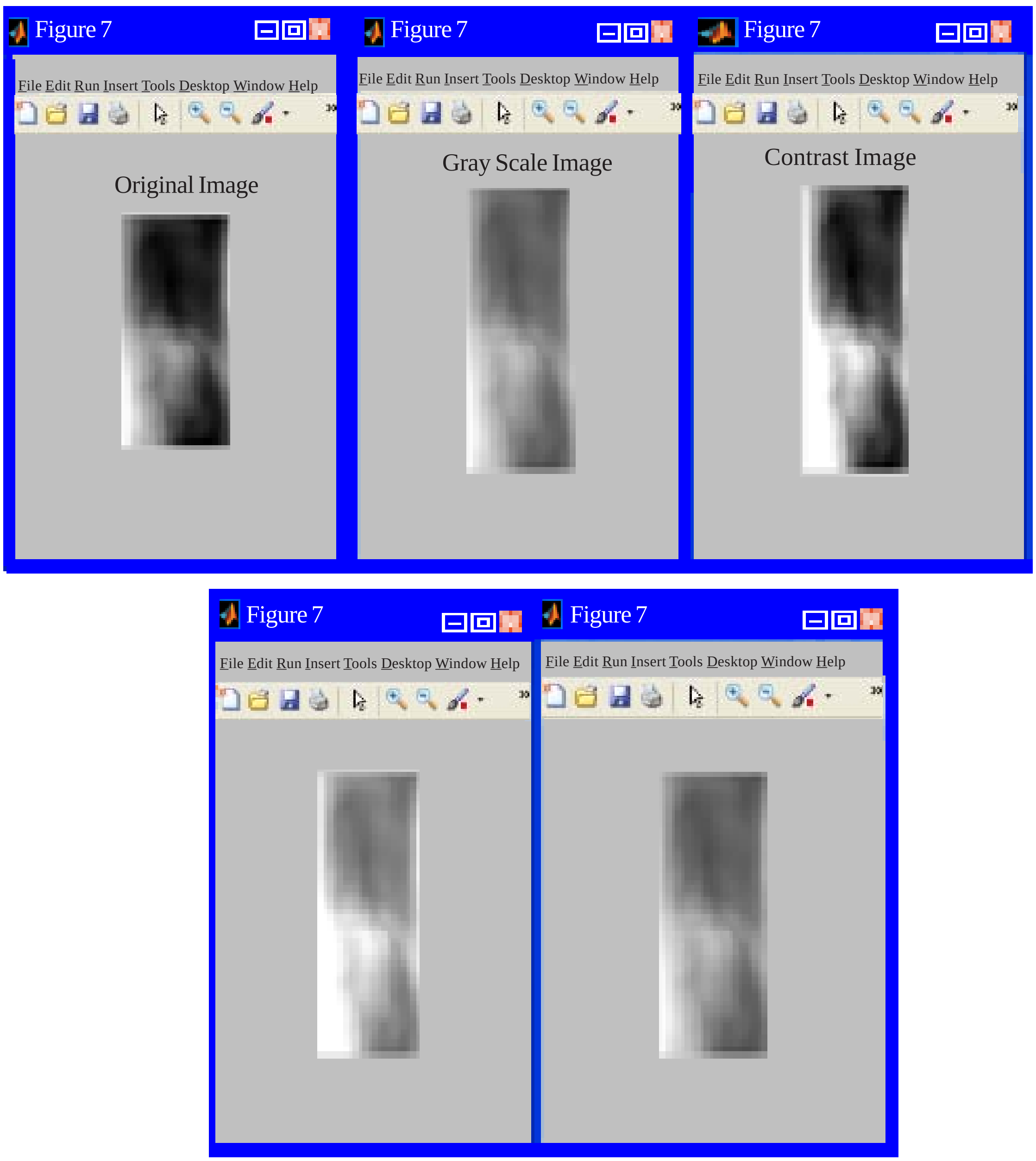

Figure 2. Preprocessing of Finger Vein Image

1. Read the initial image

2. Convert the RGB image to the Gray scale image

3. Increase the contrast of the gray scale image by multiplying the image pixel value with the constant

4. Noise removal of the contrasted image by adding the "*Salt and Pepper*" noise onto the image

5. Distortion of the image has been done by using median filter

6. Convert the image to Double precision image

The flow of preprocessing is shown below.

3.2 Image Enhancement

The preprocessed image has to further enhance to improve the contrast of the image. The mean of the Double precision image has been identified and the contrast has been increased by means of floating point accuracy (eps) of the image. The figure 6 shows the resultant contrast images are shown below based on the power of eps

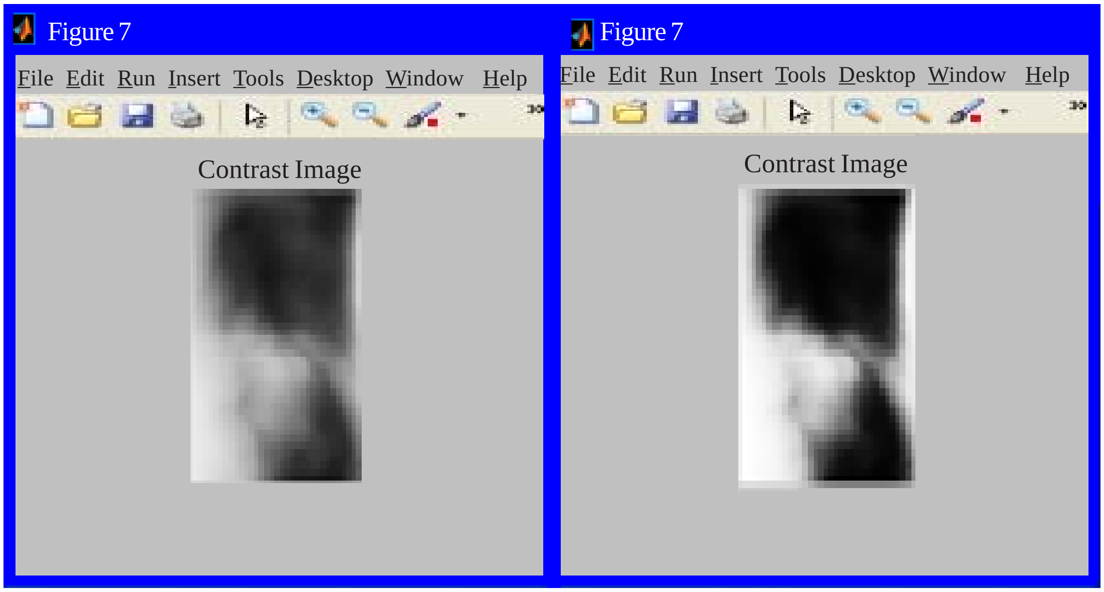

Figure 3. Enhanced Image

3.3 Gradient Image Extraction

The feature veins have been extracted from the enhanced image by means of the proposed Gradient Feature Selection Algorithm [9]. An image of a finger captured under infrared light contains not only the vein pattern but also irregular shading produced by the various thicknesses of the finger bones and muscles. The gradient direction representation provides better discrimination ability than the image intensity, and it shows that the combination of gradient directionality and intensity outperforms the gradient feature alone.

In the proposed algorithm, the gradient magnitude has been identified by the given equation

$$|G| = \sqrt{Gx^2 + Gy^2} \quad (1)$$

The Gx and Gy give the value of the n-dimensional filtering of the grascale image with the sobel operator matrices in "*Replicate*" as border options. The Sobel operator creates the own filter and performs a 2-D spatial gradient measurement of the image that corresponds to the edges. The Absolute gradient magnitude at each point of the Input gray scale image is calculated by the equation (1). The gradient is high at borders of the image and low at rest of the image as shown in the figure 7.

The Gray scale image is converted to the double precision image for finding the gradient magnitude. The double precision image along with the filter created by the sobel operator has been used to perform the magnitude calculation.

For Gx, The Sobel matrix is given as

$$Sx = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

For Gy,Thesobel matrix is the transpose of Sx, $Sy = Sx^T$

$$Sy = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

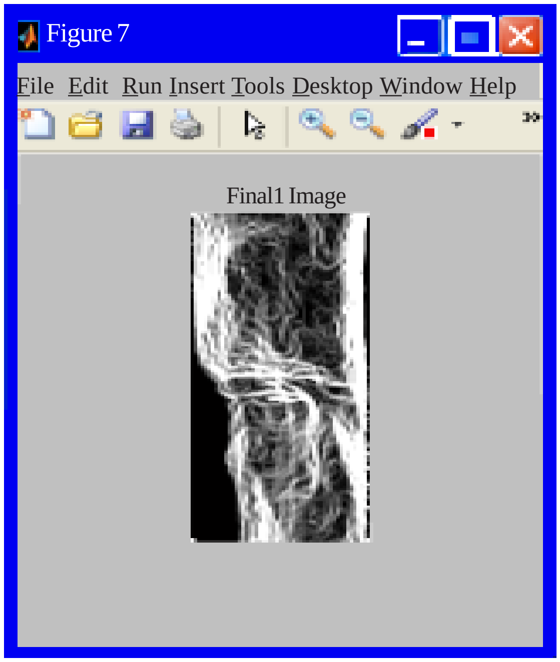

Figure 4. Gradient Feature Image

The Sx and Sy along with the Double precision grayscale image is processed separately foe Gx and Gy respectively. Based on the equation (1), The Gradient Magnitude of the gray scale image has been calculated. Figure 4.4 shows the resultant feature extracted image.

3.5 Feature Matching

Euclidean distance is considered from the center of the source cell to the center of each of the neighboring cells. True Euclidean distance is calculated in each of the distance tools. Conceptually, the Euclidean algorithm works as follows: for each cell, the distance to each source cell is determined by calculating the hypotenuse with x_max and y_max as the other two legs of the triangle. This scheming derives the true Euclidean distance, somewhat than the cell distance. The shortest distance to a source is determined, and if it is less than the specified maximum distance, the value is allocated to the cell location on the output raster.

The output values for the Euclidean distance raster are floating-point distance values. If the cell is at an equal distance to two or more sources, the cell is assigned to the source that is first encountered in the scanning process. You cannot control this scanning process.

The above description is only a conceptual depiction of how values are derived. The actual algorithm computes the information using a two-scan sequential process. This process makes the speed of the tool independent from the number of source cells, the distribution of the source cells, and the maximum distance specified. The only factor that influences the speed with which the tool executes is the size of the raster. The computation time is linearly comparative to the number of cells in the Analysis window.

4. Experimental Results

4.1 Dataset for the Experiment

The Dataset has been archived form different organizations [5]. In the dataset that had taken for i = the processing contains a set of 2110 finger samples. Each sample having the dimension of 170×76 Grayscale image. The dataset contains 106 sets where each set emphasis the 36 finger image of different dimensions. From the archiving data of finger-vein based personal authentication

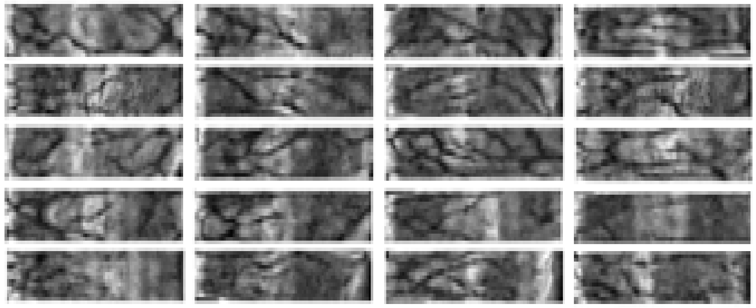
Figure 5. Finger-vein images from different fingers after preprocessing

system introduced in section 2, we eliminate some not active users from the all 1000 users because they have too few records. Because of the vacancy of common finger-vein image database for finger-vein recognition, we build an image database which contains 4500 finger-vein images from 100 individuals. Each individual contributes 45 finger-vein images from three different fingers: forefinger, middle finger and ring finger (10 images per finger) of the right hand. All images are captured using a homemade image acquisition system. The captured finger-vein images are 8-bit gray images with a resolution of 320 × 240.

4.2 Performance Evaluation

4.2.1 False Acceptance Rate (FAR)
FAR is also called False Match Rate (FMR). It mentions to the prospect that the system erroneously matches the input decoration to a non-matching template in the database. In other words, produces the percentage of inacceptable inputs which are erroneously accepted.

4.2.2 False Rejection Rate (FRR)
FRR is also called false non-match rate (FNMR). It is definite as the likelihood that the organization fails to detect a match flanked by the input pattern and an identical template in the database. That is, it procedures the percentage of valid participations which are imperfectly rejected. It is judicious that the FAR reductions but the FRR increases due to the compassion of the biometric device upsurges. In practical applications, the FAR should be very low to provide high enough confidence and the FRR must be sufficiently low. If the threshold set in the decision stage is reduced, it is expected that less false non-matches but more false accepts generated. In other words, a higher threshold corresponds to a smaller FAR and a larger FRR.

4.2.3 Receiver Operating Characteristic (ROC) Curve
The ROC curve is used for illustrating the relationship between FAR and FRR. It is a pictorial classification of the trade-off flanked by the FAR and the FRR, i.e., in a ROC curvature the vertical and horizontal axes are FAR and FRR or vice versa, separately.

4.2.4 Equal Error Rate (EER)
EER [1] is also called Crossover Error Rate (CER). It refers to the error rate at which the FAR equals to the FRR and hence can be effortlessly gained from the ROC curve. In addition, it is usually used for comparing the accuracy of devices with different ROC curves.

4.2.5 Failure to Enroll Rate (FER)
Besides FAR, FRR and ROC, there are other two factors usually considered in a vein recognition system. One is the failure to enroll rate often caused by low quality inputs. It resources the rate at which challenges to create a template from a participation is unsuccessful. The other is called failure to capture rate. It refers to the probability that the system fails to detect a correctly presented biometric input.

4.2.6 Response Time
In practical application, the response time must be taken into account. It is jointly determined by two factors. Unique is the computational complication of vein recognition algorithm and the extra is the competence of processing platform including the accepted software, performance of CPU and the scope of memory, etc.

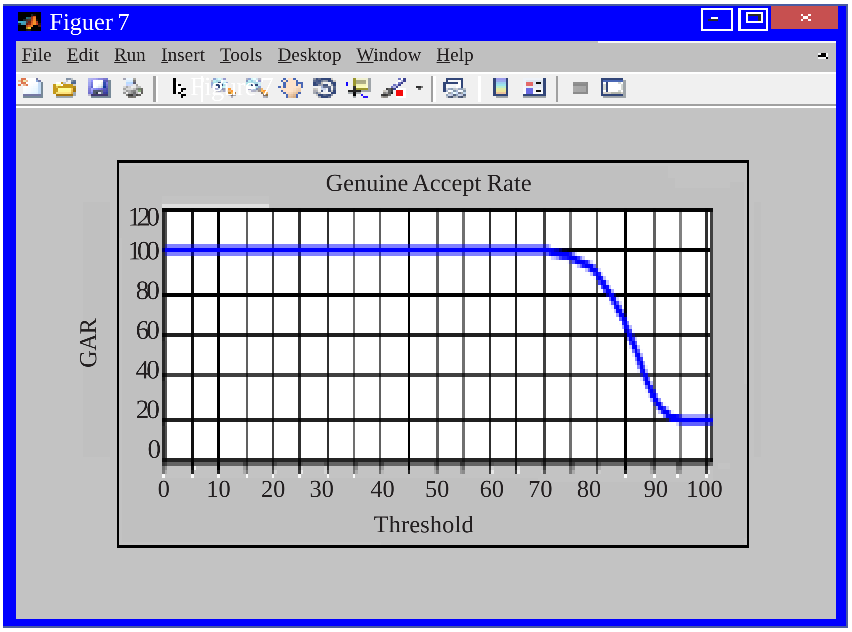

Figure 6. Genuine Accept Rate (GAR) at Different Thresholds

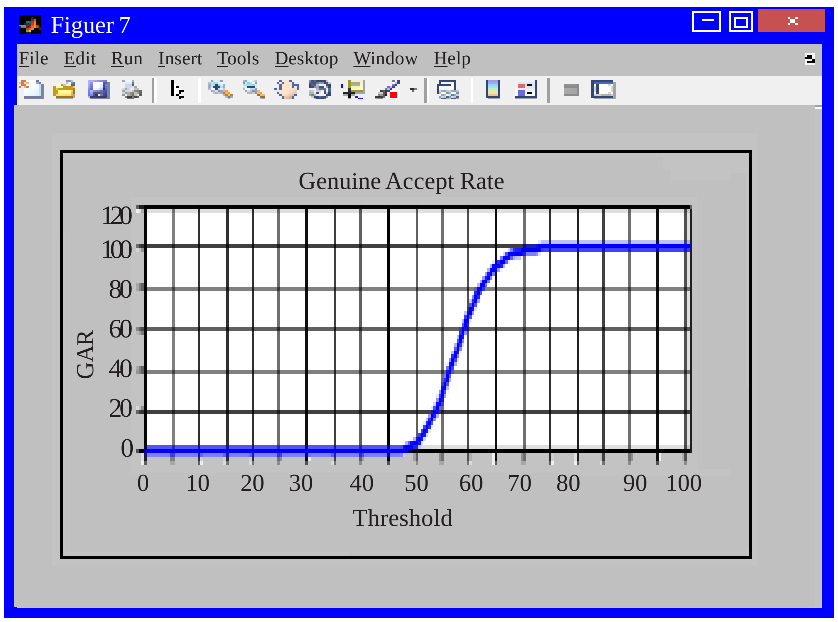

Figure 7. Genuine Reject Rate (GRR) at Different Thresholds

4.2.7 Performance for Personal Authentication

To examine the performance of proposed method for personal authentication, we did an experiment using the method described in to evaluate the false accepted rate (FAR) and false rejected rate (FRR). The proposed Algorithm has been related with the existing line tracking method then the mean curvature method for Equal Error Rate (EER). Here by comparing all the algorithms using the pattern normalization have lower error rates than the version without normalization.

4.3 Comparison with Previous Methods

Miura et al. [8] used a database that contained 1356 different infrared images of fingers. These images were achieved from persons working in their laboratory aged 20 to 40, approximately 70% of whom were male. Song's [1] finger-vein image dataset contained 5000 images together using an infrared imaging device they constructed. Seven images were taken for each of 105

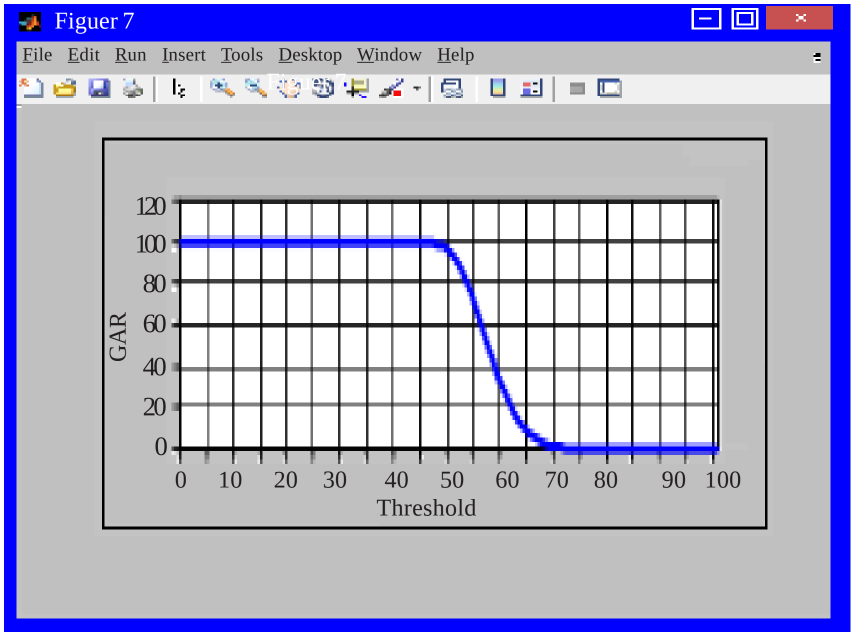

Figure 8. False Accept Rate (FAR) at Different Thresholds

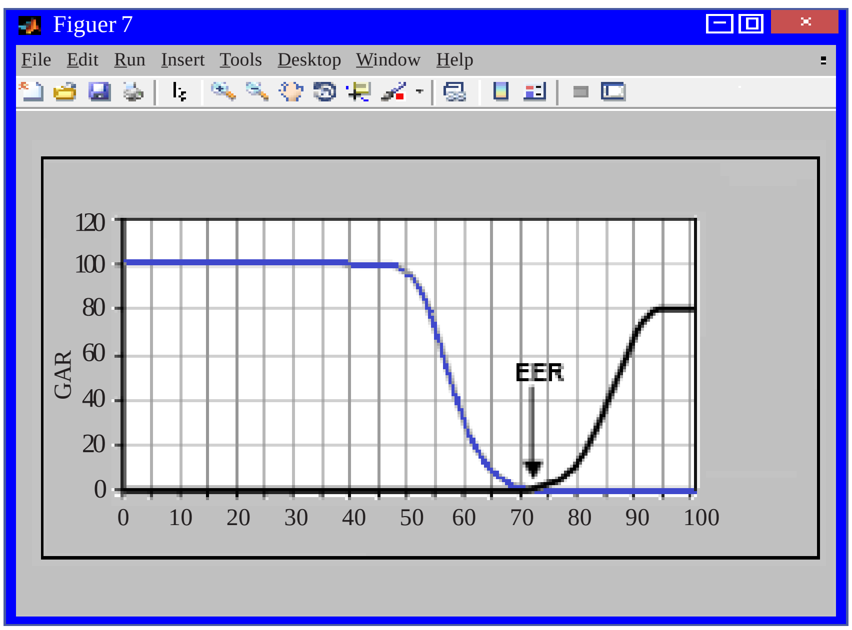

Figure 10. FRR (Type I Error) versus FAR (Type II Error)

fingers. Compared with these databases, ours is greater and the data-collection interval is longer. Thus, our database is more stimulating. Moreover, our system is implemented on a general DSP chip. Table 1 show that the average times required for feature extraction and matching in our system are 225 ms and 12 ms, respectively. For the whole system, plus the time for image capturing, the time required for the authentication of a user is less than 0.8 s. Our Feature extraction algorithm achieves an EER of 0.05%, indicating that our method significantly outperforms previous methods.

5. Conclusion and Future Enhancements

In this paper, we introduced a Gradient Feature detector to extract vein patterns. It can obtain all the points on the Gradient of vein in the image and increase the information of the feature. We also proposed a new pattern normalization method, which can

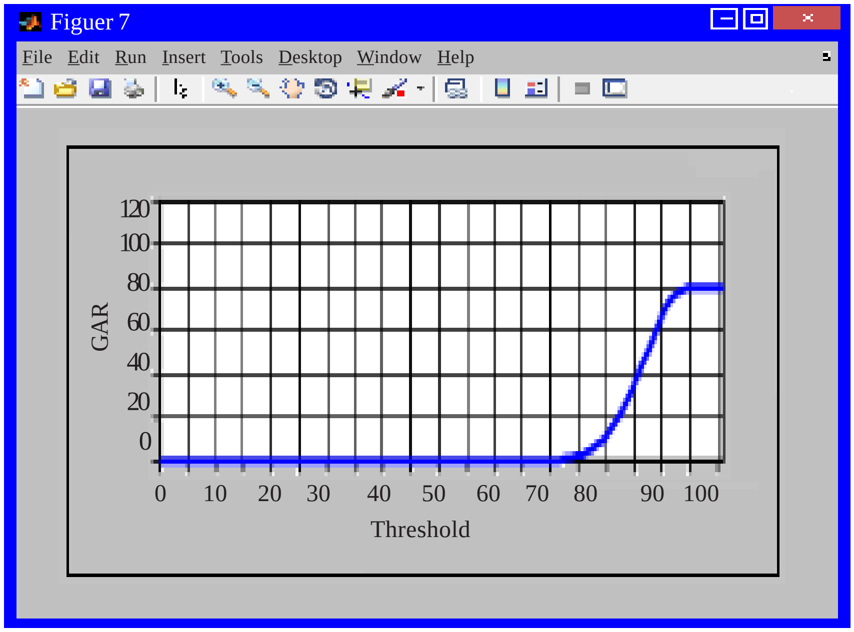

Figure 9. False Reject Rate (FRR) at Different Thresholds

Method	**Sample Images**	**EER(%)**	**Time**	
			Feature Extraction in ms	**Matching in ms**
Our method	6000	0.05	225	12
Liu and Song's Method	5000	0.07	343	13
Miura's method	1356	0.145	450	10

Table1. Recognition Rate and Response Time

reduce the irregular distortions caused by variance of finger pose. By using this method, we not only use the mutual information among different vein branches, but also treat every vein branch with independence. The proposed algorithm to extract finger-vein images by considering various parameters like vein width, position, length, pixels and intersection of veins. Our system is suitable for mobile devices and ATM's because of its low computational complexity and low power consumption. The advantage of this proposed system is more secured and confidential. The EER of 0.05% is achieved which shows the better performance than the existing vein recognition algorithms.

In future, the Curvelet Transformation [11] has been proposed instead of image enhancement using median filtering. The ROI of the captured finger image has been incorporated to the Uniform Discrete Curvelet Transformation [UDCT] to improve the efficiency of the features to be extracted. The EER of the feature enhancement can also be noticed further.

References

[1] Zhi Liu, Shangling Song. (2012). An Embedded Real-Time Finger-Vein Recognition System for Mobile Devices, *IEEE Transactions on Consumer Electronics*, 58 (2) 522-527, May.

[2] Song, W., Kim, T., Kim, H. C., Choi, J. H., Kong, J., Lee, S. (2011). A finger-vein verification system using mean curvature, *Pattern Recognition Letters*, 32 (11)1541-1547.

[3] Li, H. B., Yu, C. B., Zhang, D. M. (2011). Study on finger vein image enhancement based on ridgelet transformation. *J. Chongqing Univ. Posts Telecommun. Nat. Sci. Ed*., 23, p. 224–230.

[4] Wang, K. J., Liu, J. Y., Popoola Oluwatoyin, P., Feng, W. X. Finger Vein Identification Based on 2-D Gabor Filter. *In*: Proceedings of the 2nd International Conference on Industrial Mechatronics and Automation, Wuhan, China, 30–31 May, p. 10–13.

[5] Wang, D., Li, J., Memik, G. (2010). User identification based on fingervein patterns for consumer electronics devices, *IEEE Transactions on Consumer Electronics*, 56 (2) 799-804.

[6] Yanagawa, T. et al. (2007). Human Finger Vein Images Are Diverse and Its Patterns Are Useful for Personal Identification. MHF 2007-12, p. 1–7.

[7] http://www.fujitsu.com/global/about/rd/200506finger vein.html (accessed on2010-12-27).

[8] Miura, N. et al. (2004). Feature Extraction of Finger-Vein Patterns Based on Repeated Line Tracking and its Application to Personal Identification. *Machine Vision and Applications*, 15, p. 194–203.

[9] Lin-Lin Huanga, Akinobu Shimizu. (2003). Gradient feature extraction for classification-based face detection, *Pattern Recognition*, 36 (2003) 2501 – 2511, 2 April.

[10] Novianto, Suzuki, Maeda. (2002). Optimum estimation of local fractal dimension based on the blanket method, *Transactions of the Information Processing Society of Japan*, 43 (3) 825-828.

[11] Shangqing Wei, Xiaodong Gu. (2011). A Method for Hand Vein recognition Based on Curvelet Transform Phase Feature, December 16-18, International Conference on transportation, Mechanical, and Electrical Engineering (TMEE), Changchun, China, p. 1693-1698.