Finger-vein Pattern Matching for Human Identification

Iram Malik[1], Rohini Sharma [2], Mohd. Junaid Mir[3]
[1,2.] Information Technology Department, Maharishi Markandeshwar University (mullana)
Ambala, Haryana, India
[3.] Research scholar NIT Srinagar

***Abstract*— Biometrics is used for identification of individuals based on their physical or behavioural characteristics. Biometrics has gained importance in today's world where information security is essential. Finger-veins, one of the most well known biometric, 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. Finger-veins based biometric systems are gaining acceptance in medium to high security applications. A biometrics system for identifying individuals using the pattern of veins in a finger is proposed. It has reached an unparallel level of security, efficiency and reliable choice of high precision among the biometrics techniques. In this research a method is proposed that combines two previously developed approaches and results in enhancing the efficiency and reliability of Pattern Extraction for Human Identification. The proposed method, that is, combination of Repeated Line Tracking [2] and Even Gabor [4] extracts the finger-vein features robustly from the unclear image and the same is responsible for matching purpose in order to identify individuals. It achieves robust pattern extraction and matching and is used effectively in personal identification.**

***Keywords*—** *biometrics, finger-vein biometrics, pattern-extraction, human identification, repeated line tracking, even Gabor.*

I. Introduction

Personal identification technology is used in a wide range of systems for functions such as area access control, logins for PCs, bank ATM systems, surveillance, driver identification, e-commerce systems and many more. Biometric techniques for identifying individuals are attracting attention because conventional techniques such as keys, passwords, and PIN numbers carry the risks of being stolen, lost, or forgotten. There has been considerable research in biometrics [8], [9] over the last two decades. The list of physiological and behavioural biometric characteristics that has to date been developed and implemented is long and includes the face [10]; [11], iris [12]; [13], fingerprint [14], palm print [15], hand shape [16], voice [17], signature [18], and gait [19]. 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 [13], i.e., the biometric identifiers can be copied and used to create artefacts 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 [14]. A biometric system using finger-vein patterns, that is, patterns inside the human body is proposed. The blood vessels, as part of the circulatory system, transport blood throughout the body to sustain the metabolism, using a network of arteries, veins, and capillaries. The use of such vascular structures in the palm, palm–dorsal, and fingers has been investigated in the biometrics literature with high success [1]-[3], [6], [7]. The finger-vein patterns are believed to be quite unique, even in the case of identical twins and even between the different fingers of an individual [1]. Finger vein pattern is a promising qualified candidate for biometric-based personal identification. There are various factors that are cited for the preference of finger-vein biometrics [5]:

Anti-counterfeit: Finger veins staying underneath the skin make vein pattern duplication impossible in practice.

Active liveness: Vein information disappears with biological tissues losing liveness, which makes artificial veins unavailable in application.

User friendliness: Finger–vein images can be captured noninvasively without the contagion and unpleasant sensations

This system has the advantage of being resistant to forgery. In this system, infrared light is transmitted from the rear of a hand. One finger is placed between the infrared light source and a camera, as shown in Fig 1. As haemoglobin in the blood absorbs infrared light, the finger-vein patterns are captured as shadow patterns. The intensity of the light is adjusted using the captured image. After that, the outline of the finger is detected, the rotation of the image is corrected, and the vein pattern is extracted. A finger image captured using infrared light contains veins that have various widths and brightness, which may change with time because of fluctuations in the amount of blood in the vein, caused by changes in temperature, physical conditions, etc. To identify a person with high accuracy, the pattern of the thin/thick and clear/unclear veins in an image must be extracted equally. Furthermore, the pattern should be extracted with little or no dependence on vein width and brightness fluctuations. Conventional methods such as the matched filter [20] and morphological methods [21] can extract patterns if the widths of veins are constant. However, these methods cannot extract veins that are narrower/wider than the assumed widths, which degrade the accuracy of the personal identification. The normalized finger-vein images from the imaging setup depict a vascular network with varying thickness, clarity, and ambiguity on the topological imperfections/connections. The extraction of finger-vein features using Repeated Line Tracking [2], Maximum Curvature [3], Gabor filter [4], etc individually have given promising results. A new approach for the finger-vein feature extraction combining Repeated Line Tracking and Gabor filter is proposed. This makes pattern extraction robust and gives an improvement over these individual techniques.

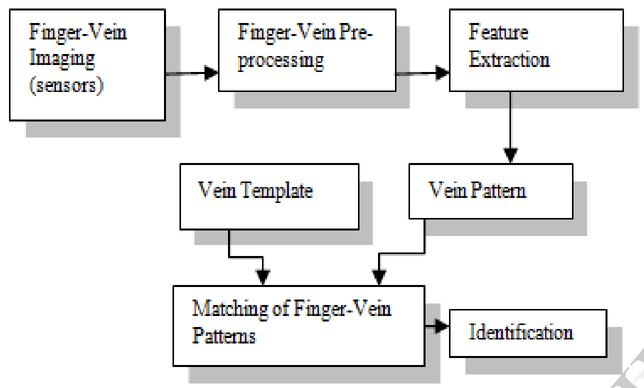

Fig. 1 Human Identification process using Finger-Vein Biometrics

The proposed technique for Human Identification is based on series of steps involving image acquisition, pre-processing, feature extraction and matching combining Repeated Line Tracking and Gabor Filter methods. This makes Pattern Extraction and matching robust. Repeated Line Tracking is implemented first for extraction of finger-vein features from the unclear image by using line tracking that starts from various positions. Although noise may also be tracked, emphasized to a smaller degree than the dark lines, yet the pattern extracted gives promising results. Multi-orientation Gabor filter is applied later on to the extracted pattern from Repeated Line Tracking in order to make the pattern extraction robust. Finally matching is done. In the matching process, the extracted pattern is converted into matching data, and these data are compared with recorded data for human identification.

II. ALGORITHMS

A. *Pattern Extraction Algorithm*

This algorithm is responsible for extracting finger-vein features by a combination of two earlier feature extracting methods viz., Repeated Line Tracking [2] and Even Gabor [4]. These two methods individually can extract finger-vein patterns but the effectivity and reliability of the extracted pattern can be increased by combining these two approaches. Pattern extracted by Repeated Line Tracking contains noise that is also tracked along with dark lines to be tracked thereby reducing its efficiency. On the other hand, Even Gabor method is also used for feature extraction but cannot be optimal in accuracy and efficiency considering the development of finger-vein recognition technology [4]. So a method is proposed that combines these two approaches and results in enhancing the efficiency and reliability of Pattern Extraction.

$F(x, y)$ is the intensity of the pixel (x, y), (xc, yc) is the position of the current tracking point of line tracking in the image, R_f is the set of pixels within the finger's outline, and T_r is the locus space. Suppose the pixel in the lower left in the image to be (0, 0), the positive direction of the *x*-axis to be rightward in the image, the positive direction of the *y*-axis to be upward within the image, and $T_r(x, y)$ to be initialized to 0.

Step 1: Determination of the start point for line tracking and the moving-direction attribute

The start point for line tracking is (xs, ys), a pair of uniform random numbers selected from R_f That is, the initial value of the current tracking point (xc, yc) is (xs, ys). After that, the moving-direction attribute D_{lr}, D_{ud} is determined. D_{lr}, D_{ud} is the parameters that prevent the tracking point from following a path with excessive curvature. Dlr and Dud are independently determined as follows:

$$D_{lr} = \begin{cases} (1,0) (if\ R_{nd}(2) < 1 \\ (-1,0)\ (otherwise) \end{cases} \quad (1)$$

$$D_{ud} = \begin{cases} (0,1)\ (if\ R_{nd}(2) < 1 \\ (0,-1)\ (otherwise) \end{cases} \quad (2)$$

Step 2: Detection of the direction of the dark line and movement of the tracking point

This step is composed of several sub-steps.

Step 2-1: Initialization of the locus-position table Tc

The positions that the tracking point moves to are stored in the locus-position table, Tc. The table is initialized in this step.

Step 2-2: Determination of the set of pixels Nc to which the current tracking point can move

A pixel to which the current tracking point (xc, yc) moves must be within the finger region, have not been a previous (xc, yc) within the current round of tracking, and be one of the neighbouring pixels of (xc, yc). Therefore, Nc is determined as follows:

$$N_c = T_c \cap R_f \cap N_r(x_c, y_c) \quad (3)$$

Where $Nr\ (xc, yc)$ is the set of neighbouring pixels of (xc, yc), selected as follows:

$$N_r(x_c, y_c) = \begin{cases} N_3(D_{lr})(x_c, y_c)\ (if\ R_{nd}(100) < P_{lr}); \\ N_3(D_{ud})(x_c, y_c)\ (if\ P_{lr} + 1 \le R_{nd}(100) < P_{lr} + P_{ud}); \\ N_8(x_c, y_c)\ \left(if\ P_{lr} + P_{ud} + 1 \le R_{nd}(100)\right), \end{cases} \quad (4)$$

where $N_8(x, y)$ is the set of eight neighbouring pixels of a pixel (xc, yc) and $N_3(D)(x, y)$ is the set of three neighbouring

pixels of (xc, yc) whose direction is determined by the moving-direction attribute D defined as (D_x, D_y))
N_3 (D) (x, y) can be described as follows:

$$N3\,(\boldsymbol{D})(x,y) = \{(\mathrm{D_x}+\mathrm{x},\mathrm{D_y}+\mathrm{y}),(\mathrm{D_x}-\mathrm{D_y}+\mathrm{x},\mathrm{D_y}-\mathrm{D_x}+\mathrm{y}),\ (\mathrm{D_x}+\mathrm{D_y}+\mathrm{x},\mathrm{D_y}+\mathrm{D_x}+\mathrm{y})\} \tag{5}$$

Parameters p_{lr} and $p_{ud...}$ (4) Are the probability of selecting the three neighbouring pixels in the horizontal or vertical direction, respectively, as N_r (sc, yc). The veins in a finger tend to run in the direction of the finger's length. Therefore, if we increase the probability that N_3 (D_{lr}) (xc, yc) is selected as N_r (xc, yc), we obtain a faithful representation of the pattern of finger veins. In preliminary experiments, excellent results are produced when p_{lr} = 50 and p_{ud} = 25.

Step 2-3: Detection of the dark-line direction near the current tracking point

To determine the pixel to which the current tracking point (xc, yc) should move, the following equation, referred to as the line-evaluation function, is calculated. This reflects the depth of the valleys in the cross-sectional profiles around the current tracking point

$$V_l = \max_{(x_i,y_i)\in N_c}\left\{F\left(x_c + r\cos\theta_i - \frac{W}{2}\sin\theta_i, y_c + r\sin\theta_i + \frac{W}{2}\cos\theta_i\right) + F\left(x_c + r\cos\theta_i - \frac{W}{2}\sin\theta_i, y_c + r\sin\theta_i - \frac{W}{2}\cos\theta_i\right) - 2F(x_c + r\cos\theta_i, y_c + r\sin\theta_i)\right\} \tag{6}$$

Where W is the width of the profiles, r is the distance between (xc, yc) and the cross section, and θi is the angle between the line segments (xc, yc) − (xc + 1, yc) and (xc, yc) − (xi, yi). Here in consideration of a thickness of the veins that are visible in the captured images, these parameters are set at W = 11 and r = 1.

Step 2-4: Registration of the locus in the locus-position table Tc and moving of the tracking point.

The current tracking point (xc, yc) is added to the locus position table Tc. After that, if Vl is positive, (xc, yc) is then updated to (xi, yi) where Vl is maximum.

Step 2-5: Repeated execution of steps 2-2 to 2-4

If Vl is positive, go to step 2-2; if Vl is negative or zero, leave step 2 and go to step 3, since (xc, yc) is not on the dark line.

Step 3: Updating the number of times points in the locus space have been tracked

Values of elements in the locus space T_r (x, y) are incremented $\forall (x, y) \in T_c$.

Step 4: Repeated execution of step 1 to step 3 (N times)

Steps 1 to 3 are thus executed N times. If the number of repetitions N is too small, insufficient feature extraction is performed. If, on the other hand, N is too big, computational costs are needlessly increased. Through an experiment, we determined that N = 3000 is the lower limit for sufficient feature extraction

Step 5: Acquisition of the finger-vein pattern from the locus space.

The total number of times the pixel (x, y) has been the current tracking point in the repetitive line tracking operation is stored in the locus space, T_r (x, y). Therefore, the finger-vein pattern is obtained as chains of high values of T_r (x, y). Figure 3.2 shows a result of finger-vein extraction. Figure 3.2.1 is the infrared image from which Figure 3.2.2 is produced as the distribution of values in T_r (x, y). The higher values are shown as brighter pixels.

Step 6: A Gabor filter can be viewed as a sinusoidal plane of particular frequency and orientation, modulated by a Gaussian envelope. So firstly we develop a Gaussian envelope by the following formula:

$$G(x,y) = \frac{\gamma}{2\pi\sigma^2} exp\left\{-\frac{1}{2}\left(\frac{x_\theta^2}{\sigma^2}\right)\right\} exp(\hat{\jmath}2\pi f_0 x_\theta) \tag{7}$$

Where

$$\begin{bmatrix} x_\theta \\ y_\theta \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \tag{8}$$

$\hat{\jmath} = \sqrt{-1}$, θ is the orientation of a Gabor filter, f 0 denotes the filter centre frequency, σ and γ respectively represent the standard deviation (often called scale) and aspect ratio of the elliptical Gaussian envelope, $x\theta$ and $y\theta$ are rotated versions of the coordinates x and y. Step 7: A set of Gabor filters as a pre-processing step for image is used and extraction of oriented image features is done. Veins hold high random characteristics in diameter and orientation, so isotropic Gaussian function is considered i.e., γ is set equal to one. For reducing diameter deformation arising from elliptic Gaussian envelope, θ varies from zero to π with a $\pi/8$ interval that is, the even-symmetric Gabor filters are embodied in eight channels.

Step 8: The generation of a combined feature map can be described as follows:

$$F(x,y)=G(x,y)\star R(x,y) \tag{9}$$

$F(x, y)$ denote a filtered result i.e., combined output, $R(x, y)$ is the output image obtained as a result of repeated line tracking and where $\star$ denotes 2D image convolution operation. It can be observed that the extracted vein structure $F(x, y)$ fits quite well in the original image vascular topologies, and the accompanying noise is suppressed very well.

B. *Matching Algorithm[2]*

In the matching process, the pattern is converted into matching data, and these data are compared with recorded data. Two methods are commonly used for matching line shaped patterns: structural matching [23] and template matching [22]. Structural matching requires additional extraction of feature points such as line endings and bifurcations. Since a finger-vein pattern has few of these points, template matching based on comparison of pixel values is more appropriate for finger-vein pattern matching.

Steps of Template Matching Algorithm:

Step 1: Labelling of the locus space.

Step 2: Spatial reduction and relabeling of the locus space.

Step 3: Matching of data.

In step 1, the locus space is binarised by using a threshold. The values of pixels labelled as parts of the background as 0 and of pixels labelled as parts of the vein regions as 255. In step2, the locus space is reduced to one third of its original size in both dimensions. This reduction is accomplished by taking the averages of all non overlapping 3 × 3 pixels. The binarised image of the locus space is turned into a smaller gray scale image. With this, new locus space is re-binarised by simply setting the threshold to 128 and finally in step3, a mismatch ratio R_m is calculated to examine whether or not two sets of data have a correlation with each other. The ratio R_m is defined as the difference between two sets of data to be matched. $R(x, y)$ and $I(x, y)$ are the values at position (x, y) of the registered and input matching data, w and h are the width and height of both sets of data, c_w and c_h are the distances in which motion in the vertical and horizontal directions, respectively, is required to adjust the displacement between the two sets of data, and the template data are defined as the rectangular region within $R(x, y)$ whose upper-left position is $R(c_w, c_h)$ and lower-right position is $R(w - c_w, h - c_h)$. The value of mismatch $N_m(s, t)$, which is the difference between the registered and input data at the positions where $R(c_w, c_h)$ overlaps with $I(s, t)$, is defined as follows:

$$N_m(s,t) = \sum_{y=0}^{h-2c_h-1} \sum_{x=0}^{w-2c_w} \{\emptyset(I(s+x, t+y), R(c_w + x, c_h + y))\} \quad (10)$$

where w = 320 and h = 240 in consideration of the finger size in the captured image, c_w and c_h are set at c_w = 50and c_h = 50 in order to adjust the finger position in the captured image by up to about 1 cm, and φ in Equation 4 is a parameter that indicates whether a pixel labelled as part of the background region and a pixel labelled as part of a vein region overlapped with each other. When P_1 is defined as the pixel value of one pixel and P_2 is defined as the pixel value of the other pixel, φ can be described as follows:

$$\emptyset(P_1, P_2) = \begin{cases} 1 \; if \; |P_1 - P_2| = 255 \\ 0 \qquad otherwise \end{cases} \quad (11)$$

The minimum value of mismatch Nm, which is the smallest $N_m(s, t)$ calculated under the condition that the template overlaps with the input matching data $I(x, y)$ at all positions, can be defined as follows:

$$N_m = \min_{0 \le s < 2c_w, 0 \le t < c_h} N_m(s,t) \quad (12)$$

The definitions given above, the mismatch ratio R_m is defined as follows:

$$R_m = N_m \Big/ \left\{ \sum_{j=t_0}^{t_0+h-2c_h-1} \sum_{i=s_0}^{s_0+w-2c_w-1} \emptyset(I(i,j), 0) + \sum_{j=c_h}^{h-c_h-1} \sum_{i=c_w}^{w-c_w-1} \emptyset(0, R(i,j)) \right\} \quad (13)$$

Where s_0 and t_0 are s and t such that Equation 7 is minimized. As is shown by Equation 7, R_m is described as the ratio between N_m and the total number of pixels that are classified as belonging to the vein region in the two data sets.

III. EXPERIMENTS

To check the performance of the proposed technique several parameters are used. Parameters evaluate the technique in terms of Genuine Acceptance Rate (GAR) and False Acceptance Rate (FAR).

A. Evaluation Parameters

- False Acceptance Rate

FAR is the ratio of the number of unauthorized users accepted by the biometric system to the total of identification attempts to be made. This is also known as type 2 error, False Acceptance Rate is when an imposter is accepted as a legitimate user, This happens when the system find that the biometric data is similar to the template of a legitimate user. FAR is calculated by:

$$FAR(\lambda) = \frac{number\ of\ false\ attempts}{total\ number\ of\ attempts}$$

For example, if FAR=10^{-1}, it means that out of 10 identification attempts, 1 illegitimate user is identified as legitimate.

- Genuine Acceptance Rate

Genuine Acceptance Rate (GAR) is an overall accuracy measurement of a biometric system. It is calculated by the formula:

GAR = 1 – FAR.

GAR is important because it is the chief measurement of precision. We can directly compare separate biometric systems by setting their threshold so that the FAR is at a specific value. The GAR is then measured at this specific FAR. If we are comparing two different systems, the system with the highest GAR rate is considered to be the most accurate. GAR is commonly measured at different FAR intervals.

The proposed technique for Human Identification is based on series of steps involving image acquisition, pre-processing, pattern extraction and matching combining Repeated Line Tracking and Even Gabor methods. This technique has been applied to gray scale images and gives satisfactory results. The technique has been implemented on a set of 2 gray scale 320x240 images of .bmp extension. The performance of the technique has been evaluated and graphically represented on the basis of two measures which are – Genuine Acceptance Rate (GAR) and False Acceptance Rate (FAR) in the form of bits. The experiments has resulted in a good GAR (Genuine Acceptance Rate) for its corresponding FAR (False Acceptance Rate) showing improved reliability that frustrate spoofers by developing biometrics that are highly individuating; yet at the same time, highly effective and robust.

The GAR and FAR of input Finger-Vein image for the three approaches considered viz., Repeated Line Tracking, Gabor Filter method and Combined Method is shown in the tables 1 and 2. If we compare the GAR for the corresponding FAR of the input finger-vein images, we can say that combined approach gives best results.

TABLE 1
Comparison Of Different Human Identification Approaches (Repeated Line Tracking, Even Gabor And Combined Method) By Means Of GAR Vs FAR Of Input Finger-Vein Image (Index Finger).

Input Image 320x240	Repeated Line Tracking (previous method)		Even Gabor (previous method)		Combined Approach (Repeated Line Tracking+ Even Gabor)	
	FAR	**GAR**	**FAR**	**GAR**	**FAR**	**GAR**
index_1.bmp	0	0.53	0	0.5	0	0.73
index_1.bmp	10^{-4}	0.55	10^{-4}	0.65	10^{-4}	0.83
index_1.bmp	10^{-3}	0.65	10^{-3}	0.78	10^{-3}	0.88
index_1.bmp	10^{-2}	0.80	10^{-2}	0.85	10^{-2}	0.89
index_1.bmp	10^{-1}	0.94	10^{-1}	0.97	10^{-1}	0.97
index_1.bmp	10^{0}	1	10^{0}	1	10^{0}	1

Table 2
Comparison Of Different Human Identification Approaches (Repeated Line Tracking, Even Gabor And Combined Method) By Means Of Gar Vs Far Of Input Finger-Vein Image (Middle Finger)

Input Image 320x240	Repeated Line Tracking (previous method)		Even Gabor (previous method)		Combined Approach (Repeated Line Tracking+ Even Gabor)	
	FAR	**GAR**	**FAR**	**GAR**	**FAR**	**GAR**
middle_1.bmp	0	0.25	0	0.33	0	0.5
middle_1.bmp	10^{-4}	0.3	10^{-4}	0.4	10^{-4}	0.5
index_1.bmp	10^{-3}	0.4	10^{-3}	0.5	10^{-3}	0.6
index_1.bmp	10^{-2}	0.6	10^{-2}	0.7	10^{-2}	0.79
middle_1.bmp	10^{-1}	0.86	10^{-1}	0.92	10^{-1}	0.95
middle_1.bmp	10^{0}	1	10^{0}	1	10^{0}	1

Fig. 2 shows the graphic representation of ROC (Receiver Operating Characteristics) of index finger. ROC demarcates plot between GAR and its corresponding FAR of an input Finger-Vein image. The horizontal axis shows the FAR and vertical axis shows the corresponding range of GAR. The red line shows the plot for Combined Method (Repeated Line Tracking + Even Gabor) where as blue line shows plot for Even Gabor method and pink line shows plot for Repeated Line Tracking. The graph shows that combined method gives optimum result.

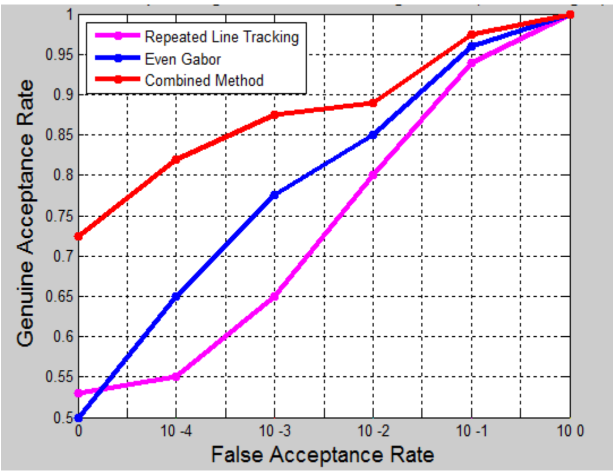

Fig.2 Graphic representation of GAR versus FAR for index finger.

Fig. 3 shows the graphic representation of ROC (Receiver Operating Characteristics) of middle finger. ROC demarcates plot between GAR and its corresponding FAR of input Finger-Vein image. The horizontal axis shows the FAR and vertical axis shows the corresponding range of GAR. The red line shows the plot for Combined Method (Repeated Line Tracking + Even Gabor) where as blue line shows plot for Even Gabor method and pink line shows plot for Repeated Line Tracking. The graph shows that combined method gives optimum result.

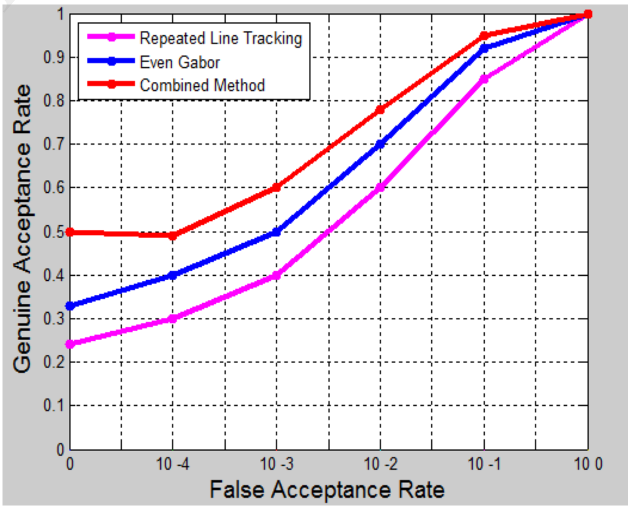

Fig.3 Graphic representation of GAR versus FAR for middle finger.

The performance analysis of the whole process resulted in improved reliability for Human Identification by means of the proposed method that is, combined method (Repeated Line Tracking + Even Gabor) thereby showing effective and optimum results when compared to individual techniques viz., Repeated Line Tracking and Even Gabor method.

IV. CONCLUSION

The new approach for Human Identification combining Repeated Line Tracking and Gabor filter results in improving performance and reliability and at the same time is highly effective and robust. The proposed technique is based on series of steps involving image acquisition, pre-processing, pattern extraction and matching combining Repeated Line Tracking and Even Gabor methods. This makes Pattern Extraction and matching robust. Repeated Line Tracking is implemented first for extraction of finger-vein features from the unclear image by using line tracking that starts from various positions. Although noise may also be tracked, emphasized to a smaller degree than the dark lines, yet the pattern extracted gives promising results. Multi-orientation Gabor filter is applied later on to the extracted pattern from Repeated Line Tracking in order to make the pattern extraction robust. Finally matching is done by implementing Template matching technique. In the matching process, the extracted pattern is converted into matching data, and these data are compared with recorded data for human identification. It is observed that the proposed technique comes up with good GAR values that give promising results and an improvement over the earlier individual methods.

V. FUTURE SCOPE

Although Finger-vein Biometrics is one of the latest biometric technologies, it has already established both technical and statistical feasibility, in the very near future the combination of Finger-Vein Biometric with other Biometric technologies will result in a multimodal system with very high accuracy especially for security concerns in sensitive areas.

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