A Robust Vein Pattern-based Recognition System

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***Abstract*—This paper presents an efficient human recognition system which makes use of vein patterns obtained from the back of the hand. It has used a new reflection-based image capturing environment to ensure high quality images through least effort and cost. The proposed recognition system automatically detects the region of interest (ROI) from the image and does the necessary preprocessing to extract features. Extracted features from ROI are compared to obtain the matching score and to take the decision. It is tested on a data set of 4950 images collected from 990 individuals. The accuracy of the recognition system is found to be 99.11% with a false acceptance rate of 0.4%.**

***Index Terms*— Recognition System, Vein Pattern, Active Contouring, Line Fitting, Forking Point.**

I. Introduction

The existent biometric traits with variable capabilities have proven successful over time. Traits like Face, Ear, Iris, Fingerprints, Signatures etc., have dominated the world of biometrics over the years. But each of these biometric traits has its shortcomings. Ear and iris pose a problem during sample collection. Not only is the iris based system expensive but it also needs high attention or otherwise it has a high failure to enroll rate. In case of ear data, it is hard to capture a non-occluded image in real time environment. In face recognition systems, there exist some limitations like effects of aging or background, etc [13]. Fingerprints, though reliable and accepted worldwide, still lack automation and viability as they are also susceptible to wear and aging. Further, signatures are liable to forgery.

Vein patterns, on the other hand, have the potential to surpass most of the above mentioned issues. Apart from the size of the pattern, the basic geometry always stays the same. Unlike fingerprints, veins are located underneath the skin surface and are not prone to external manipulations. Vein patterns are also almost impossible to replicate because they lie under the skin surface [8].

Reflection based techniques for capturing veins from the back of the hand have been suggested in [1][3][15] while Watanbe [18] has collected templates from the front. Badawi [1] has also tried to establish the uniqueness of vein patterns using patterns from the palma dorsa. The data acquisition technique mentioned in [1] is based on a clenched fist holding a handle to fix the hand during image capture. This technique, however, has limitations with respect to orientation of the hand. Substantial works in this field have been done by Wang and Leedham [15][16][17]. In these, thermal imaging of the complete non fisted hand has been done using infrared light sources. Generally, near infra-red lamps of intensity-value ranging from 700nm to 900 nm in wavelength are used to design such a system [16]. It has been observed that the images captured through a reflection based system, as proposed in [15], would never produce consistent results owing to excessive noise generated due to unnecessary surface information unless an apt noise removal algorithm is applied. A system of capturing images from the front of the hand has been proposed in [14]. However, in this case the palm prints may interfere with the pattern of the veins.

Numerous attempts have also been made in the recent past to capture vein templates and successfully employ them as recognition traits [3][11]. There are nooks and flaws with either the image processing techniques employed or the matching strategies that are used. Importantly, it can be noted that the failure to enroll (FTE) rate, which is an important parameter for any biometric trait, is never reported by any of the recent research papers.

Failure to enroll rate is the percentage of the population which fails to complete the enrollment for a biometric solution or application. Failure can be due to physical differences, to lack of training, environmental conditions or ergonomics. It is mandatory in the current practical scenario to consider the FTE for every proposed system. If any system requires extensive training for its usage or fails to collect usable data consistently-it shouldn't qualify. This can be envisioned or presumed as the reason for small sample sizes in [1][3][11][14] [15][16][17].

This paper proposes a reflection based technique which uses a specially designed hardware set-up for the purpose. It is found that the FTE is almost immaculate and the images captured are of a very high quality. The 'usability' of all samples is excellent. The collected data is processed by a variety of image processing operations that are low in complexity and high on performance. An automated segmentation technique along with an efficient noise removal technique is considered at the pre processing stage. It uses a minutiae based matching technique. It has been tested on a database of 4950

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doi:10.4304/jcp.7.11.2711-2718

images obtained from 990 subjects. Its accuracy is found to be 99.11%.

The paper is organized as follows. Section 1 presents the proposed recognition system based on vein patterns. The experimental results of the proposed system have been analyzed in Section 3. The concluding remarks are stated in the final section.

II. Proposed System

Like any other biometric system, the vein pattern based recognition system consists of four major tasks and they are (i) Image Acquisition, (ii) Preprocessing on image data, (iii) Feature Extraction, and finally (iv) Matching. Figure 1 shows the flow diagram of the system.

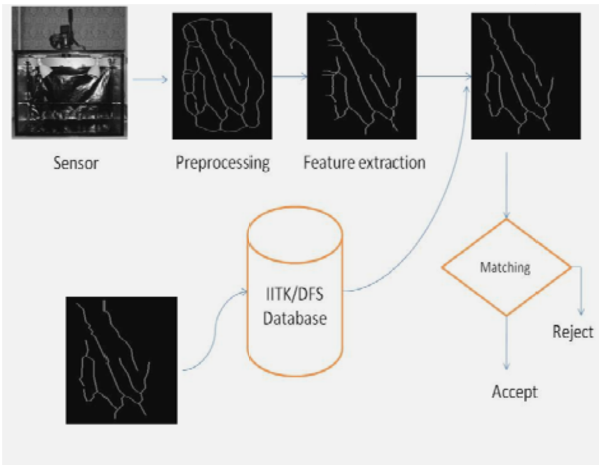

Figure 1. Flow Diagram of the Proposed System

A. *Image Acquisition*

Image quality plays an important role in any recognition system. For the proposed system, a hardware set up is designed in such a way that one can get good quality of vein patterns from the back of a hand. The data acquisition procedure relies on the fact that the hemoglobin present in the vessels of the human hand appears black under infra red (IR) light. An acquisition system can use IR lamps of wavelength 700-1000 nm and the light can be reflected on the desired surface or transmitted to it [2][15][16]. It can also be absorbed from the opposite side [14]. In order to collect a large quantity of images-the FTE rate is the most important consideration at this stage.

The set-up of the proposed reflection based system has been designed for collecting data is shown in Figure 2. It consists of a box with a hole cut on its top surface and an open front face. A metal rod has been fixed joining the centre of the side walls of the box. There is a fixed stand in the back of the box that holds the tripod at approximately 10 inches away from the rod in the centre of the box. The camera when mounted on the tripod focuses through the hole in the roof of the box. The interior surface of the roof of the box is fitted with two infra-red lamps of wavelength 850 nm. These are connected to an external battery. Lamps when lit provide a complete and consistent infra-red environment for the hand that can be placed on the rod/plinth, under the camera. Inside of the box is covered by black glazed paper to provide all the acquired images with the desired contrast and a uniform background. The cylindrical plinth has been blackened as well. This rod also comes with two movable cardboard partitions that can fix the hand between them under the camera orifice. There is also an almost opaque black curtain covering the open front surface of the box. It enables the hand to slip in and also ensures a uniform and unadulterated environment of infra-red light for the subject’s hand.

Parameters required for getting consistent data are carefully studied in making the set-up and are given below:

- The distance between the camera and the lamp.
- The position of the lamp.
- The fixed area for the placement of the hand.
- The focal length and the exposure time of the camera lens.

These parameters are kept constant throughout and hence, ensure uniformity in the collection process. The fisted hand makes the veins pop out and hence, they appear clearly in the collected images. The set-up ensures zero ambient interference. The consistent background ensures images in good contrast. The digital SLR ensures images of high resolution. The non-complexity of the system ensures a negligible FTE rate , i.e., an image with a useful region of interest (ROI) gets registered in almost all cases irrespective of the skin color, skin disease related scars or discolorations, or the thickness of a subject’s skin. Relative translation or rotation of the hand is countered in the hardware set-up as well.

The only factor due to which an inconsistency can occur during image acquisition is the size of a subject’s hand since there is no control over the girth and thickness of a human hand in a practical scenario. As a result, the exact distance between the object and the camera’s lens can never be pre-determined or fixed. To counter this issue, necessary arrangements have been made in the set-up. The focal shift of the camera which can be fine tuned to the order of millimeters ensures the *relative* prevalence of the desired conditions. Also, it has been observed that tattoos on hands interfere with successful image capture.

B. *Preprocessing*

The color image acquired through a camera generally contains some additional information which are not required for the desired vein patterns. So there is a need to extract the region of interest (ROI) from the acquired image and finally, to convert it into a noise free thinned image from which one can generate the venal tree. This section presents a method to extract such a venal tree from the colored palm image. It consists of seven major tasks and they are (i) Segmentation, (ii) Image Enhancement (iii) Binarization and Filteration, (iv) Dilation and Skeletonization, (v) Venal pattern generation, (vi) Connecting disjointed edges, and (vii) Noise removal.

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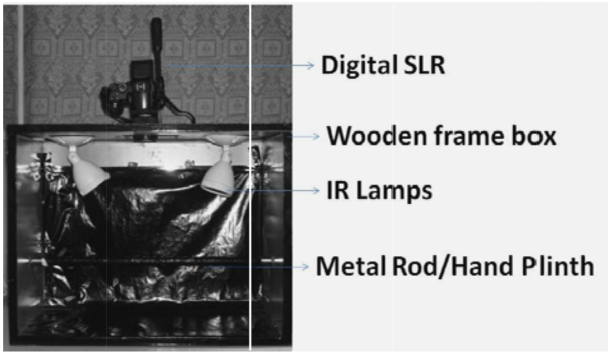

Figure 2. Image Acquisition Set-up

Segmentation is the first and the most vital step. Badawi [1] has considered the skin component of the image as the region of interest (ROI) while Wang and Leedham [15] have used anthropometric points of a hand to segregate an ROI from the acquired images. It has been observed that all well known techniques for ROI selection employ inconsistent techniques and need manual intervention during processing [3][11]. The segmentation technique proposed in this paper is used to segregate the skin area from the acquired image and to select the ROI in a systematic manner. It also gets rid of any kind of manual intervention. It is the fusion of the technique based on active contouring proposed by Kass et. al. [7] with a common cropping technique. Active contouring works on the principle of intensity gradient. To begin with, the user initializes a contour anywhere in the image. This is supposed to bend, expand or wither in order to detect the boundary of an object with respect to time. The initialized active contour can be defined as a parametric curve $v(s) = [x(s), y(s)], s \in [0, 1]$ which aims eventually to minimize the following energy function.

$$E_{contour} = \int_0^1 \frac{1}{2}(\eta_1 |v'(s)|^2 + \eta_2 |v''(s)|^2) + E_{ext}(v(s))ds \quad (1)$$

where η_1 and η_2 are weights to control the relative importance of the elastic and bending ability of the active contour respectively; $v'(s)$ and $v''(s)$ are the first and the second order derivatives of the initial curve equation, and E_{ext} is the external energy derived from the image. In order to minimize the above function, E_{ext} needs to hold smaller values at the object boundary.

E_{ext} for the image which depends on gradient, needs to be calculated beforehand. For instance, considering an image $I(x, y)$, where (x, y) are some spatial co-ordinates, the typical external energy to lead the contour towards the edges, can be defined by

$$E_{ext} = -|\nabla I(x,y)|^2 \quad (2)$$

where ∇ is the gradient operator. For any colored image the intensity gradient which takes the maximum of the gradients of R, G and B bands at every pixel, is given by

$$\nabla I = \max(|\nabla R|, |\nabla G|, |\nabla B|) \quad (3)$$

Therefore, it is clear that the gradient obtained using the above equation is the driving force for the active contour. Any active contour that minimizes $E_{contour}$, must satisfy the following Euler equation

$$\eta_1 v''(s) - \eta_2 v^{iv}(s) - \nabla E_{ext} = 0 \quad (4)$$

where $v^{ii}(s)$ and $v^{iv}(s)$ are the second and the fourth order derivatives of $v(s)$. The energy of the contour is a resultant of the forces acting on it. Considering the above equation as a force balancing equation, one gets $F_{int} + F_{ext} = 0$ where

$$F_{int} = \eta_1 v''(s) - \eta_2 v^{iv}(s) \quad (5)$$

and

$$F_{ext} = -\nabla E_{ext} \quad (6)$$

It can be noticed that F_{int} is the internal force responsible for the stretching and bending of the curve whereas F_{ext} is the external force that drives the contour towards the desired features in the image. The contour's movement is a function of the gradient of the image. A sharp shift in gradient would mark the equalization of both the forces that are acting simultaneously on the curve. The energy function of the contour, $E_{contour}$, can be minimized when these two antagonistic forces equalize each other. The contour finally rests around the desired object and the foreground and the background are clearly segregated.

The active contour deforms itself with time to exactly fit around the object. It can also be represented as a time varying curve.

$$v(s, t) = [x(s, t), y(s, t)] \quad (7)$$

where $s \in [0, 1]$ and is arc length and $t \in R^+$ is time. The step of active contouring is followed up by the iterative use of a cropping tool which helps to extract the object in the foreground from the background [7]. This extraction is done automatically and almost flawlessly.

However, it should be noted that the active contouring snake has been modified from the one proposed by Kass et al [7]. Instead of initiating the snake from the outside in, it executes in reverse, after initiating it from the centre of the image as in [14]. Since all images are exactly of the same size, the initiation can always be done automatically for any image. This minimizes manual intervention and subjective selections during segmentation, making the results more accurate. Figure 3 shows the extracted segmented image which is termed as Region of Interest (ROI).

The extracted ROI of the colored image is converted into a grey scale image using any well known method. Gaussian filtering technique is used on the grey scale image for enhancement and normalization into a predefined mean and variance. This type of enhancement is required to negate any anomalies during image capture

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viz. light conditions, ambient interference, camera shake, etc. Figure 4 shows the enhanced and normalized image.

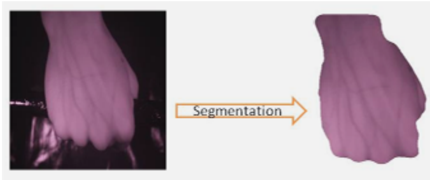

Figure 3. Segmented Image

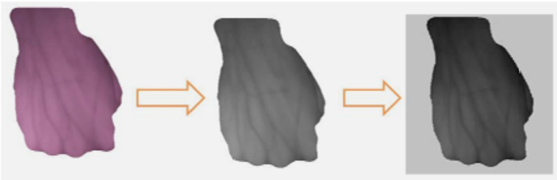

Figure 4. Grey scale Conversion and Normalization

The resultant image is then binarized. Edges are located in the image and an edge map is created. However, it is observed, that along with the desired veins there may exist many additional components like salt and pepper noise, blobs, stains, and a few unconnected edges. Median filtering can be used to remove salt and pepper type noises [4]. Figure 5 shows the conversion of the grey scale image to a noise free binary edge map.

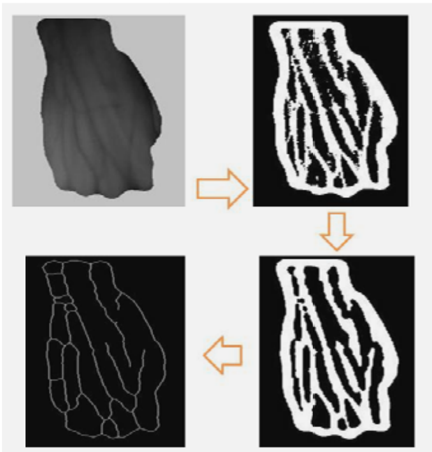

Figure 5. Dilation and Skeletonization

For further processing, it is now required that the venal tree be freed from the outline of the hand. The venal tree can be thus defined, as the skeletonized connected pattern of veins-sans the boundary of the hand. This pattern alone is required for further usage. It is this potential of the proposed system to capture legible venal trees immaculately, subject after subject that makes it superior and robust. From the skeleton of the hand, the skeletonized veins are extracted. A vertical and a horizontal line (one pixel thick) are run through each coordinate of an image alternatively. The coordinates of the first and the last image pixels encountered by the line, in both axes, are then turned black and the venal tree is computed. All structures inside the hand boundary contain the venal tree along with some isolated islands and segments. In order to obtain only desired components among veins for the tree, all connected components are labeled and others are discarded. In order to do so the CCL (Connected Component Labeling) algorithm [9] has been modified to determine all the connected components in an image. This modified algorithm detects and removes all isolated and disconnected components of size less than a specified threshold. Figure 6 shows the generated venal pattern for some skeletonized veins.

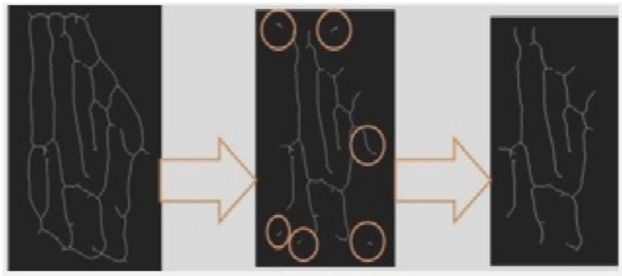

Figure 6. Venal Tree Generation

It is observed that the desired vein patterns on the palma dorsa are line segments of considerable length. However, there is a possibility that these continuous line segments may have some break in them after edge detection. These breaks may be as little as a missing pixel but are relevant. Therefore, it is necessary to join these broken edges. There are two well known algorithms which can be used to link broken edges. The first one is based on Hough transformation [12] while the other one is a recursive algorithm [10]. The algorithm based on Hough transformation promises to be faster but it results in an invariable shift in the position of the feature points (forking points) that are to be extracted subsequently. But any shift in the original feature point is considered as a violation of the authenticity of the original sample. The recursive algorithm proposed in [10] has no such problem. In this algorithm, different 'edge contours' are to be located in a binary edge image. Whenever an edge confronts an ending or a splitting, the edge contours initiate and terminate. The process of edge contour detection is explained below.

For an edge contour, *E,* if the starting and end points are (x_1,y_1) and (x_2,y_2) then a line segment is drawn joining the points. A deviation is charted out for this line segment from the actual contour and the point of maximum deviation is marked. If the obtained deviation is within the permissible threshold, the line segment is allowed to stay; otherwise, the coordinate of the point of maximum deviation is considered as the new end point of the line segment. The process is then repeated with new end points. The permissible threshold is set to as low as 2 pixels only to protect the originality of the sample. The equation of the line having (x_1,y_1) and (x_2,y_2) as end points of the line segment can be represented as

$$x(y_1 - y_2) + y(x_1 - x_2) + y_2x_1 - y_1x_2 = 0 \tag{8}$$

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The maximum deviation of a point *(u,v)* on the edge contour from the fitted line segment can be calculated by

$$d = \frac{r}{D} \quad (9)$$

where $r = u(y_1 - y_2) + v(x_1 - x_2) + y_2x_1 - y_1x_2$ and $D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$

This task helps to break down an edge contour into line segments where each one adheres to the original data with the specified permissible deviation. It also gives a compact representation to the acquired vein patterns. The image containing edges with the fitted lines can be used for the selection of feature points and for the removal of surface noise. Figure 8 shows all the individual edge contours of a pattern marked distinctly in color.

Reflection based image collection systems are prone to surface noise. It has been observed that coarser body hair appear as black as the veins. These hairs inhibit the successful capture of a precise skeleton since they appear as noise connected to the venal tree. Such patterns have to be removed to get rid of spurious feature points. Rejection of samples due to such type of noise may increase the failure to enroll (FTE) rate of the system. Therefore, it becomes mandatory to remove the noisy edges due to the body hair which can be done by the proposed line fitting algorithm. Figure 7 reveals the proposed line fitting algorithm distinguishes between ridges and displays them in a graph for observation. As observed in Figure 7, there exist some horizontal segments in cohesion to the main venal tree. These are smaller in size. Any edge contour below a particular size (threshold) is considered to be a false edge and is deleted from the hand's dorsal surface.

It has been observed that this method has successfully removed the noise created by the body hair. Experimentally, it has been observed that contours of length less than 20 (pixels) are found to be false edges.

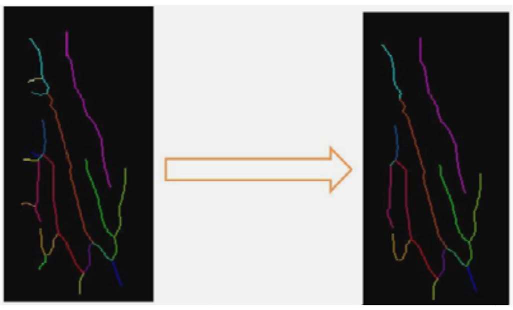

Figure 7. Individual Edge Contours marked in color

Figure 8 shows the results obtained through this method where the horizontal encircled lines indicate the noise due to hair. The algorithm for the process of line fitting is stated below.

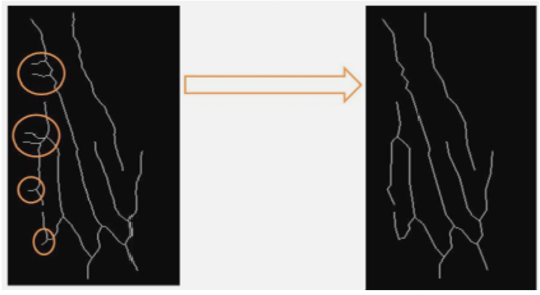

Figure 8. Noise Removal through Line-fitting

ALGORITHM 1: Line Fitting

Input: Venal pattern image
Output: The line fitted vein pattern image *L*

1. Divide all the ridges in the pattern into n individual contours E_i with end points (x_{i1}, y_{i1}) and (x_{i2}, y_{i2}) where i = 1, 2, ...,n and n is the total number of contours in a pattern. This individualization is based on the information that whenever an edge confronts an ending or a splitting, the edge contour initiates or terminates. Set i=1.
2. Choose an edge contour E_i.
3. Draw a virtual line between (x_{i1}, y_{i1}) and (x_{i2}, y_{i2}).
4. Calculate the distance of line from each point (u_k, v_k) in the contour using formula:
$$d_k = \frac{r_k}{D}$$
where
$r_k = u_k(y_{i1} - y_{i2}) + v_k(x_{i1} - x_{i2}) + y_{i2}x_{i1} - y_{i1}x_{i2}$ and $D = \sqrt{(x_{i1} - x_{i2})^2 + (y_{i1} - y_{i2})^2}$
5. Find the value of k for which $d = \max(d_k)$
6. If $d > deviation$ then draw a line in image L between (x_{i1}, y_{i1}) and (u_k, v_k) . Set $x_{i1} = u_k$, $y_{i1} = v_k$ and go to Step 4 to fit line for the rest of the edge contour.
7. If $d \leq deviation$ for all points (u_k, v_k) on the edge contour, draw a line between (x_{i1}, y_{i1}) and (x_{i2}, y_{i2}) in L.
8. $i = i + 1$ and go to Step 3 until $i \leq n$.

C. Feature Extraction

Patterns obtained as a result of processing are utilized for obtaining valuable feature points which aid in matching. Feature points need to be located first and then their characteristics need to be calculated. Features can be extracted in two steps. A feature point is a point where a

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vein segment splits into two or more segments. This splitting point is termed as a 'forking point' since the word bifurcation may not always be applicable for vein patterns. This section discusses the technique to locate these feature points and calculate the *angle of split*.

Forking Detection

In this sub-section a technique which extracts the forkings from the skeleton image has been presented. In a processed image an ROI contains some thinned lines/ridges. Ridge forking in the ROI can be considered as a feature and can be determined by computing the number of *arms originating from a pixel*. This can be represented as A. One can find the number of arms by examining the local neighborhood of each ridge pixel using a 3×3 window.

For a pixel P, if its neighboring pixels of a 3×3 window are scanned in an anti-clockwise direction as:

P_4	P_3	P_2
P_5	P	P_1
P_6	P_7	P_8

The A for a pixel P can be computed by

$$A = \frac{1}{2}\sum_{i=1}^{8}|P_i - P_{i+1}| \ , \ (P_1 = P_9) \qquad (10)$$

It can be seen that there are four possible values of A and they represent the following:

A	*refers to*
1	Ridge Termination
2	Continuous Ridge
3	Forking Point (with 2 arms)
4	Forking Point (with 3 arms)

There could be more arms originating from a particular forking point and the subsequent value of A could go higher [14]. But, such a case has not been observed in the existing database. Thus, a given pixel P is termed as a ridge forking for a vein pattern if the value of A for the pixel is 3 or more. This ridge forking pixel is considered as a feature point which can be defined by (x, y) where x and y are its coordinates. This method of forking extraction is applied on ROI to extract all relevant and true forking points which are represented by their respective coordinates x and y.

Angle Calculation

All ridges emitting out of a forking point (usually three) move in their own direction at different angles with respect to their x-axis. Each forking point (x,y) can be treated as the termination point of three line segments with end points (x_0,y_0) and (x_i,y_i) where $i=1,2,3$. Let θ_i gives the slope of these lines, then θ_i can be calculated by:

$$\theta_i = \tan^{-1}\frac{y_i - y_0}{x_i - x_0} \qquad (11)$$

This value of angle gives information regarding the connectivity of the ridge/arm and also the angle it forms with its x-axis. Similarly, the angle can be calculated for all the arms emitting out of each forking point in the obtained vein pattern.

These angles along with the coordinates of their respective forking points are considered as features of the vein pattern. Suppose there are n forking points in a given vein pattern. Then, for each forking point there are three feature points, each of 3 tuple (x, y, θ). Figure 9 depicts the process of angle calculation.

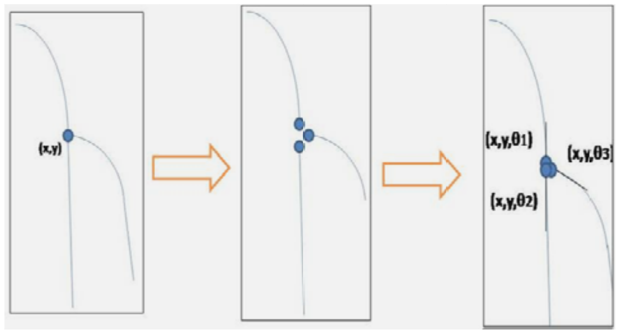

Figure 9. Angle Calculation of Each Arm from a Forking Point

D. Matching

Suppose, A and B are two patterns having n and m features respectively. Let, $A= \{a_1, a_2, a_3, ..., a_n\}$ be the pattern to be tested against $B =\{b_1, b_2, b_3, ..., b_m\}$from the database where a_i, and b_i represent 3-tuple feature of A and B respectively. Euclidean distance measure is used for ascertaining a match. For a given feature point a_i in A, it tries to find a point b_j, $j=1, 2, 3...m$ in B such that both the distance between two points and their difference are not only minimum but also less than their pre-defined thresholds. If such a point b_j exists, then one can conclude that these two points are matched. Let w_{ij} be the distance between a_i and b_j. A similar approach is employed using the values of the angles of stretch.

In this approach, however, there is a possibility to get match with more than one a_i with a particular b_j and this leads to register false match. In order to get rid of this type of false match, the following approach has been considered.

Let W be an $n\times m$ matrix where w_{ij} is the distance between a_i and b_j if a_i and b_j are matched and is $+\infty$ if these points are not matched. Further, let there be another $n\times m$ matrix RM_{ij}, known as relation matrix such that

$$RM_{ij} = \begin{cases} 0 & \text{if } w_{ij} = \infty \\ 1 & \text{otherwise} \end{cases} \qquad (12)$$

Define array R and C such that $R_i = \sum_{j=1}^{m} RM_{ij}$ and $C_j = \sum_{i=1}^{n} RM_{ij}$. Then R_i gives the number of elements of B which can be considered as matched with a_i and C_j gives the number of elements of A which are matched with b_j. Let us define an array SELECT of n elements where $SELECT_{[i]}$ is used to indicate whether there is a match of a_i with any element in B, then $SELECT_{[i]}$ is set

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to 1 so that a_i is not considered again by another element of B for matching. At any stage, it can be noted that if R_i is the minimum positive integer among all elements of R and $SELECT_{[i]}$ is 0 which indicates that there is no element in B matched with a_i till that stage, then one should select at this stage an element from B which is matched with a_i.

In order to select the element from B for matching with a_i, one searches the element C_j in C such that C_j is minimum in C and there is a relation between a_i and b_j, i.e., $RM_{ij}=1$. To avoid the selection of a_i again by any other element of B, $SELECT_{[i]}$ is set to 1, all elements of the i^{th} row and of the j^{th} column of RM are set to 0. In this way one can select the match of a_i with an element b_j in B such that no other element of B selects a_i as a match point.

This process is repeated till there is a possibility of an element in B to be matched with an element in A, i.e., until all elements of RM are *zero*. Algorithm 4 provides the matching strategy. Let C be the number of points of A which are matched with points of B uniquely. It can be noted that number of such matches can at most be $min\ (m, n)$. Then the match score rate, M_s, between A and B can be defined by

$$M_s = \frac{C}{\min(m,n)}\ X\ 100\ \% \qquad (13)$$

If M_s is found to be less than some threshold value, one can conclude that A and B are not matched.

III. EXPERIMENTAL RESULTS

The proposed system has been tested against the IITK database [14] to analyze its performance. The database consists of 4950 images obtained from 990 individuals. Out of these, 990 are used as query samples. Its accuracy against various thresholds has been plotted in a graph which is shown in Figure 10. It is observed that an accuracy of 99.11% is achieved through this system. Graphically, it is also found from Figure 11 that the value of FAR for which the system achieves maximum accuracy is 0.4%. Finally, the ROC curve is drawn for different values of GAR against FAR and is given in Figure 12.

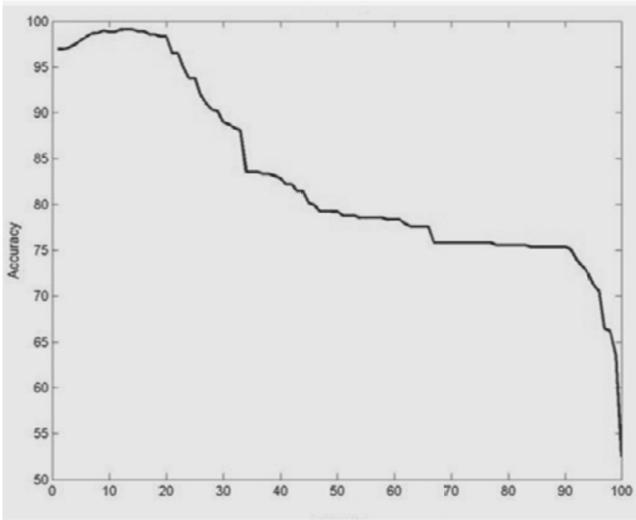

Figure 10. Graph of Accuracy

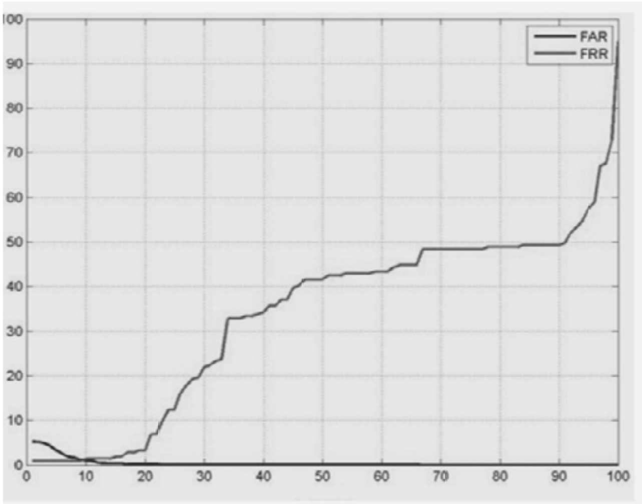

Figure 11. Graph representing FAR and FRR

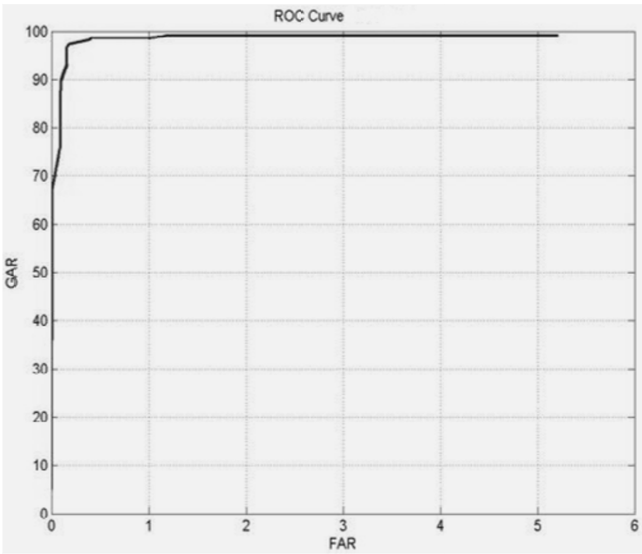

Figure 12. The ROC Curve

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IV. Conclusion

This paper has introduced vein patterns from the back of the hand to design a robust biometric system. it has presented a hardware set-up of an immaculate acquisition model, an automated segmentation technique, an effective noise removal method, a new feature point selection approach and an accurate matching technique. The proposed system has been tested on a sizable database of 4950 images from 990 subjects and has achieved an accuracy of 99.11% with a very low FAR of 0.4%. The system is found comparable to previous ones with significant additional improvements.

Acknowledgment

The authors wish to thank Mr. Sandesh Gupta and Dr. M.S. Rao for their guidance and valuable help. This work was funded and supported by the Directorate of Forensic Science, New Delhi and the Indian Institute of Technology Kanpur, Uttar Pradesh.

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