

# Development of a Biometric Security System using Finger Vein Extraction to Build a Class Attendance System

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**Abstract**— *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 repeated line tracking that starts from various positions and Decision tree. The system is implemented by a class attendance system.*

**Keywords**— *Repeated Line Tracking, Decision Tree*

## I INTRODUCTION

In this age of increasing in information growth, the main social problem at hand is how to solve human identity recognition and safeguard information. The conventional identity recognition contains two type methods, namely; contents based which is password, code and so on, and possessing based, which are smart card, licence, and so on.

Nevertheless, with this development growth, many of these conventional identity recognition techniques abuse begin to appear. Both code and password may not be remembered or stolen. Though passwords are still widely used, their lack of proper implementation has seen it gaining immense criticism (Bonneau and Preibusch 2010). In case of certificate key and smart card, there is probability of been stolen, forged or lost. This has motivated the identity recognition technology using human features to overcome the shortcomings of traditional identity recognition.

Human in-built biologically and conduct characteristics like face, vein, DNA, voice, sign and gait are used to detect person character in the event of optics, biosensor, inoculation of computer etc. Thus, this technology has proved to be better in terms of accuracy, suitability, timelines, privacy, safety, and trustworthiness than the uses of certificate, code and card for identity recognition. Biometric is the science that deals with verifying and establishing the individuality of a man via physiological features such as fingerprint, hand vein, face and finger vein or behavioural traits such as handwriting, speech, and signature, for automatic recognition. Hence, Biometric recognition deals with any norms, which a person can be distinctively identified by assessing single or multiple distinguishing biological traits. It is used in lieu of the username-password recognition scheme, as it is nearly impossible to replicate a person's biological features. The law enforcement agencies first abducted biometric systems in 1970s to investigate criminals with the uses of fingerprint recognition (Jain and Kumar 2010). However, in the current biometric technologies advancement with the growth of threats in information security, the biometric application systems have proliferated into the physical and logical access control domains.

In this present time, forensics are rapidly and increasingly evolving biometric application technologies such as in criminal

identification and prison security. Also, Biometrics have the capability to remain extensively approved in a very wide range of national applications, for example, immigration regulation, national ID, access control, voting system, driver licensing system and banking security. These technologies have been made conceivable by unstable advances in processing power and have been made important by the close broad interconnection of computers around the world.

Finger vein biometric recognition system is most prominent among biometric methods. Finger vein is a biometric trait for individual recognition from the security and suitability perspective. The vein pattern in finger utilizes as a novel component for recognition and validation. Veins are commonly unseen by individuals because they are hidden under the skin surface, not liable to external alteration, and the patterns are much tougher to duplicate than other biometric virtues. The vein pattern for every human being is distinct.

They offer additional consistent quality for a secure biometric recognition system due to its stability, great resistance to criminal altering and uniqueness. The exactness, security level, and long-term dependability of finger vein are higher than any other biometrics.

## II REVIEW

(Kaur and Verma 2014) through the finger – vein system built a security system to keep valuable data save. The finger vein of the person having access to the data is taken and saved in a data base, then if the data is to be accessed, there must be a verification process that must occur before an access is given. The system receives the finger vein of the person who wants access to the data and the process is called image processing, the image is imported with an optical scanner or by digital photography, Analysis and manipulation of the image is done. This includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs. The Output stage is the last stage in which result can be altered image or report that is based on image analysis. The finger vein is therefore compared to the one in the data base, if there is a match access is granted. But if the finger veins do not match, access is denied.. (Yilong et al 2014) worked on the survey of finger vein recognition. The authors examined the system in the following ways: image acquisition and public data bases, and feature extraction and matching. (Bansal and Kaur 2013) Worked on Finger Vein Recognition Using Minutiae Extraction and Curve Analysis. , they created a data base in which several finger vein capture could be saved, the collected a finger vein sample and saved it in the data base, the created a system for authentication. Since the legit finger vein had been saved in the data base, they created a system to receive a sample of finger vein, then the received data goes through processing and therefore compared to the original data in the data base. If there is a match, access will be granted but if otherwise access will be denied. (Brindha 2017)

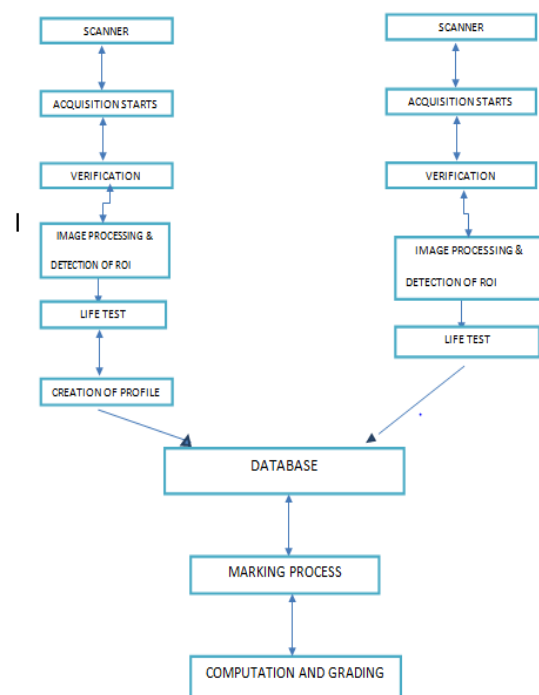
used Neighbourhood elimination technique to eliminate redundancy. Neighbourhood elimination technique is employed for the purpose of removing the redundant information while keeping the effective source information for subsequent processing. This technique is applied on the normalized point-set of finger vein. For each point of finger vein, those points that lie within the neighbourhood of a certain radius are removed. In order to determine the neighbours of each specific point, the spatial information is used. (Yang et al 2018) reviewed all the processing steps of the finger vein recognition which are image acquisition, pre-processing, feature extraction, and matching. The authors also worked on conventional, machine learning and deep learning-based finger vein recognition approaches. Algorithms were assessed in the key recognition steps of image acquisition, pre-processing, feature extraction and matching. In image acquisition, the light transmission method was considered to be the best for capturing the high-quality image. In image pre-processing, ROI extraction methods and image enhancement methods were reviewed. In addition, the conventional feature extraction methods were classified into four groups (i.e., vein-based method, local binary-based method, dimensionality-based method and minutiae-based method) and introduced in detail. For the matching stage, the distance-based matching methods and classifier-based matching methods were both exemplified. (Miura et al 2004) propose a method of personal identification based on finger-vein patterns. The authors placed a finger in between an infrared light source and a camera. As haemoglobin in the blood absorbs the infrared light, the pattern of veins in the palm side of the hand is captured as a pattern of shadows. The captured images contain not only vein patterns but also irregular shading and noise. The shading is produced by the varying thickness of finger bones and muscles. Therefore, regions in which the veins are and are not sharply visible exist in a single image. The authors proposed a method that solves the problems described above. The method is based on line tracking, which starts at various positions. Local dark lines are identified, and line tracking is executed by moving along the lines, pixel by pixel. When a dark line is not detectable, a new tracking operation starts at another position. All the dark lines in the image can be tracked by repeatedly executing such local line tracking operations. Finally, the loci of the lines overlap and the pattern of finger veins is obtained statistically. As the parts of the dark lines are tracked again and again in the repeated operations, they are increasingly emphasized. (Sharma et al. 2014) acquired a finger vein image, but the acquired image is noisy, with rotational and translational variations resulting from unconstrained imaging. Therefore the acquired image was subjected to the following pre – processing steps: Segmentation of ROI, Translation and orientation alignment, and Image enhancement to extract stable/reliable vascular patterns. Then the enhanced a normalized ROI images are employed for features extraction. (Akintoye et al. 2018) proposed an approach that efficiently classifies the finger vein pattern based on the extracted features and improves finger vein recognition system. After the capturing of the finger vein image, they processed the image captured. By this process they were able to remove every noise and after this they did the feature extraction using repeated line tracking method, then to the matching/ recognition process. Recognition or matching process takes place after features have been extracted from the vein image. This stage evaluates the correlation between the features of input finger vein image and the formerly registered finger vein images in the database. The authors also proposed a new method that will enhance the weaknesses of the system. The proposed method is called the k-mean classification technique. (Janes and Junior 2014) presented an identification system based on the dorsal hand vein pattern recognition, using a

low cost camera to capture images with near-infrared (NIR), curvelet transforms for feature detection of images and random forest classification method.

They captured only the light from an image in the infrared spectrum. For this, they selected a conventional camera model ST-CAM001 for the Cyber Comp with 470k resolution pixel. Since this is a conventional camera, its use is capturing images in the visible light spectrum and to eliminate any kind of light, for example infrared and ultraviolet. Our first step was to remove the infrared filter which was located on the camera lens just above the image pickup sensor for the camera to allow the passage of this type of light, and adapt a high pass filter, blocking the visible light to the eye thus allowing only the passage of infrared light.

### III METHODOLOGY

The proposed project is built by applying the architecture model below



The proposed model for the finger vein biometrics. (1).

The system is sub divided into two aspects which are Registration process and Verification, marking and grading process.

1. Registration process: In this aspect, the students offering a particular course finger vein image is taken, together with their personal data such as Name, Matric number e.t.c. The details taken is then stored in the Database.
2. Verification, marking and grading process: In this aspect, the student details are verified from the database, the attendance is marked and the grading is done according to the prescription of the lecturer.

**Decision Tree:** A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements.

A decision tree is a flowchart-like structure in which each internal node represents a “test” on an attribute (e.g. whether a

coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules.

Tree based learning algorithms are considered to be one of the best and mostly used supervised learning methods. Tree based methods empower predictive models with high accuracy, stability and ease of interpretation. Unlike linear models, they map non-linear relationships quite well. They are adaptable at solving any kind of problem at hand (classification or regression).

Decision tree is employed during authentication. It is used to decide what to do if the authentication is successful and what to do if not.

**Repeated Line Tracking:** A cross-sectional profile of a vein appears as a valley. The depth of the valley varies with the shading in the image. However, the valley remains detectable. Therefore, the profiles give us a robust method of finger-vein detection.

The line-tracking operation starts at any pixel in the captured image. The current pixel position is called the “current tracking point”, and it is moved pixel by pixel along the dark line. The depth of the cross-sectional profile is checked around the current tracking point. Pixel  $p$  is a neighbor of the current tracking point in the upper-right direction. Cross-sectional profile  $s-p-t$  looks like a valley. Therefore, the current tracking point is on a dark line. The direction of this dark line can be detected by checking the depth of the valley with varying  $\theta_i$ . This gives us the  $\theta_i$  at which the valley is deepest. After that, the current tracking point moves to the pixel closest to this direction, pixel  $p$ . If the valley is not detectable in any direction  $\theta_i$ , the current tracking point is not on a dark line and a fresh tracking operation starts at another position.

For smooth line tracking, an attribute that restricts increases in the global curvature of the locus is added to the tracking point. This attribute is called “the moving-direction attribute”. In concrete terms, this restricts selection from among the eight neighboring pixels of the next tracking-point position.

If only a single line-tracking operation is conducted, only a part of veins within the image will be tracked. To solve this problem, vein-tracking sequences are started at various positions that are determined so that the line-tracking trials are conducted evenly across the image.

The current tracking point may track a region of noise by chance. Statistically, however, the dark lines are increasingly tracked more often with repeated operations. This makes for the robust extraction of patterns of finger veins.

The number of times that each pixel has become the current tracking point is recorded in a matrix named the “locus space”. The size of the locus space is the same as the number of pixels in the captured images. The total number of trials on which each pixel has become the current tracking point is recorded in the corresponding matrix element. Therefore, an element of the locus space that is more frequently tracked has a higher value.

Therefore, line tracking from all pixels in the finger region is not required. Eliminating some start points for line tracking reduces the computational costs while retaining accuracy in extraction.

Line tracking starts randomly at different positions. To find the dark line line tracking executed by moves along the direction of vein pattern pixel by pixel. The idea is to trace the veins in the image by chosen directions according to predefined probability in the horizontal and vertical orientations, and the starting position, called seed is randomly selected; the whole process is repeatedly done for a certain number of times.

The method of feature extraction is described in this section.  $F(x, y)$  is the intensity of the pixel  $(x, y)$ ,  $(x_c, y_c)$  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  $Tr$  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  $Tr(x, y)$  to be initialized to 0.

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

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

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

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

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

The details of each step are described below.

Step 1: Determination of the start point for line  $tr$

The start point for line tracking is  $(x_s, y_s)$ , a pair of uniform random numbers selected from  $R_f$ . That is, the initial value of the current tracking point  $(x_c, y_c)$  is  $(x_s, y_s)$ . After that, the moving-direction attribute  $Dlr$ ,  $Dud$  is determined.  $Dlr$ ,  $Dud$  are the parameters that prevent the tracking point from following a path with excessive curvature.  $Dlr$  and  $Dud$  are independently determined as follows:

$(1, 0)$  (if  $Rnd(2) < 1$ ).

$Dlr = (1)$

$(-1, 0)$  (otherwise);

$(0, 1)$  (if  $Rnd(2) < 1$ ).

$Dud = (2)$

$(0, -1)$  (otherwise),

where  $Rnd(n)$  is a uniform random number between 0 and  $n$ .

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

This step is composed of several substeps.

Step 2-1: Initialization of the locus-position table  $T_c$

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

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

Step 2-4: Registration of the locus in the locus-position table

$T_c$  and moving of the tracking point

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

Details of these steps are described below.

Step 2-1: Initialization of the locus-position table  $T_c$

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

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

A pixel to which the current tracking point  $(x_c, y_c)$  moves must be within the finger region, have not been a previous  $(x_c, y_c)$  within the current round of tracking, and be one of the neighboring pixels of  $(x_c, y_c)$ .

Therefore,  $N_c$  is determined as follows:

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

where  $N_r(x_c, y_c)$  is the set of neighboring pixels of  $(x_c, y_c)$ , selected as follows:

$$N_r(x_c, y_c) = \quad (4)$$

$$N_3 \quad (Dud)(x_c, y_c) \text{ (if } plr+1Rnd(100) < plr+pud);$$

$N3(Dlr)(xc, yc) \quad (\text{if } Rnd(100) < plr);$   
 $N8(xc, yc) \quad (\text{if } plr + pud + 1 \leq Rnd(100)),$   
 where  $N8(x, y)$  is the set of eight neighboring pixels of a pixel  $(xc, yc)$  and  $N3(D)(x, y)$  is the set of three neighboring pixels of  $(xc, yc)$  whose direction is determined by the moving-direction attribute  $D$  ( defined as  $(Dx, Dy)$  ).  $N3(D)(x, y)$  can be described as follows:

$$\begin{aligned}
 N3(D)(x, y) = \{ & (Dx +x, Dy +y), \\
 & (Dx -Dy +x, Dy -Dx +y), \\
 & (Dx +Dy +x, Dy +Dx +y)\}. \tag{5}
 \end{aligned}$$

Parameters  $plr$  and  $pud$  in Eq. 4 are the probability of selecting the three neighboring pixels in the horizontal or vertical direction, respectively, as  $Nr(sc, yc)$ . The veins in a finger tend to run in the direction of the finger's length. Therefore, if we increase the probability that  $N3(Dlr)(xc, yc)$  is selected as  $Nr(xc, yc)$ , we obtain a faithful representation of the pattern of finger veins. In preliminary experiments, excellent results are produced when  $plr = 50$  and  $pud = 25$ .

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.

$$\begin{aligned}
 VI = \max_{(xi, yi) \in Nc} & \\
 W & \\
 F(xc +r \cos \theta_i - \sin \theta_i, yc +r \sin \theta_i + \cos \theta_i) & \\
 \frac{2}{W} & \quad \frac{2}{W} \\
 +F(xc +r \cos \theta_i + \sin \theta_i, yc +r \sin \theta_i - \cos \theta_i) & \\
 \frac{2}{W} & \quad \frac{2}{W} \\
 -2F(xc +r \cos \theta_i, yc +r \sin \theta_i) , & \tag{6}
 \end{aligned}$$

where  $W$  is the width of the profiles,  $r$  is the distance between  $(xc, yc)$  and the cross section, and  $\theta_i$  is the angle between the

line segments  $(xc, yc) - (xc + 1, yc)$  and  $(xc, yc) - (xi, yi)$ . In this paper, 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  $VI$  is positive,  $(xc, yc)$  is then updated to  $(xi, yi)$  where  $VI$  is maximum.

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

**TOOLS USED**

The software was written in C using Virtual Basic. The system is built to run on the Windows OS. And as a result, it can only work for laptops, and they must have the following requirements:

- Windows OS: Window 7 and above.
- RAM: 2GB (Minimum)

Other tools used are:

- Integrated development environment (IDE): Visual Code/Sublime Text
- Visual Studio 2019
- Hitachi FV Biometric Scanner
- CloudScanr for FV Scanner

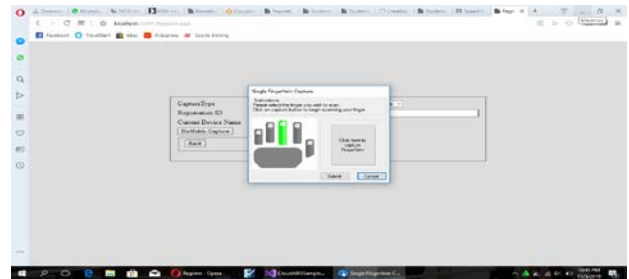


Figure 1.1. This shows the capturing process of the finger vein image.

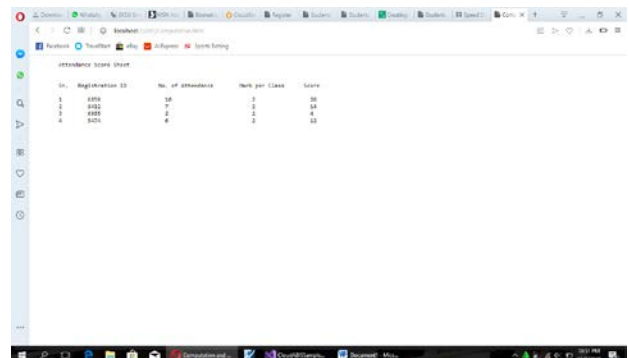


Figure 1.2. This shows the computation and the grading process of the system

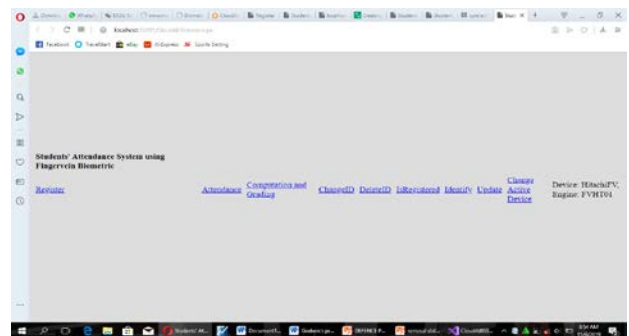


Figure 1.3. This is the home page of the system.

**EXPERIMENTAL TESTING/DISCUSSION**

The system was tested by scanning a large number of finger vein images. The false acceptance rate FAR and false rejection rate was evaluated. The system is able to achieve a false acceptance rate FAR of about 3% and false rejection rate of about 3.2%.

**VI CONCLUSION**

With the above facts, we could say the design of this system will further strengthen the finger vein biometric system. The system successfully registered users, marked the attendance and computed and graded the users accordingly.

## REFERENCES

1. Bonneau J, Preibusch S, editors. The Password Thicket: Technical and Market Failures in Human Authentication on the Web. WEIS; 2010
2. Dr.S.Brindha. (2017). Finger Vein Recognition. International Research Journal of Engineering and Technology. Volume: 04 Issue: 04.
3. Gongping Yang, Kashif Shaheed, Imran Qureshi, Jie Gou, Yilong Yin and Hangang. (2018) A Systematic Review of Finger Vein Recognition Techniques. MPID Publications.
4. Gupta P. and Gupta P. 2015. An Accurate Finger Vein Based Verification System. Digital Signal Processing. 38 43-52.
5. Jain AK, Kumar A. Biometrics of next generation: An overview. Second Generation Biometrics. 2010;12(1):2-3
6. Jose Anand, T. G. Arul Flora<sup>2</sup> and Anu Susan Philip<sup>3</sup> (2013), Finger-Vein Based Biometric Security System, International Journal of Research in Engineering and Technology. eISSN: 2319-1163 | pISSN: 2321-7308
7. Kayode Akinlekan Akintoye, Mohd Shafry Mohd Rahim and Abdul Hanan Abdullah. (2018). Challenges of finger Vein Recognition System: A Theoretical Approach. International Journal of Emerging Technology and Advanced Engineering
8. Kejun Wang, Hui Ma, Oluwatoyin P. Popoola and Jingyu Li. (2011). Finger Vein Recognition. INTECHOPEN
9. Komal Bansal and Supreet Kaur (2013), Finger Vein Recognition Using Minutiae Extraction and Curve Analysis, International Journal of Science and Research (IJSR). ISSN (Online): 2319-7064.
10. Komal Turka and Gurpreet Kaur. (2014). Finger Vein Detection Using Repeated Line, Even Gabor and Median Filter. International Journal of Computer Science and Information Technologies. Vol. 5 (3).
11. Lee EC, Park KR. Image restoration of skin scattering and optical blurring for finger vein recognition. Optics and Lasers in Engineering. 2011; 49(7):816–28.
12. Liu Z et al. Finger vein recognition with manifold learning. Journal of Network and Computer Applications. 2010; 33(3):275–82.
13. Manpreet Kaur and Geetanjali Babbar (2015), Finger Vein Detection using Repeated Line Tracking, Even Gabor and Multilinear Discriminant Analysis (MDA), International journal of computer science and information technology. Vol. 6 (4).
14. Naoto Miura, Akio Nagasaka and Takafumi Miyatake (2004). Feature extraction of finger-vein patterns based on repeated line tracking and its application to personal identification. Machine Vision and Applications
15. Podgantwar UD, Raut U. Extraction of Finger-Vein Patterns using Gabor Filter in Finger vein Image Profiles. 2013.
16. Prabjot kaur and Mr. Prince Verma (2014), Human Identification with Finger Veins Using Repeated Line Tracking, Even Gabor and Automatic Trimap Generation Algorithms, International journal of computer science and information technology. Vol. 5 (6).
17. Ricardo Janes and Augusto Ferreira Brandao Junior. (2014). A Low Cost System for Dorsal Hand Vein Patterns Recognition Using Curvelets. First International Conference on Systems Informatics, Modelling and Simulation
18. Sameer Sharma, Mr. Shashi Bhushan, Ms. Jaspreet Kaur. (2014). Improved Human Identification using Finger Vein Images International Journal of Computer Science and Mobile Computing. Vol.3 Issue.1.
19. Trung Huynh. (2011) Finger Vein Authentication System. University Of Plymouth Books.
20. Verma D. and Dubey S. 2012. Two Level Centre of Gravity Computation-an Important Parameter for Offline Signature Recognition. International Journal of Computer Applications. 54(10).
21. Xuebing W, Jiangwei Z, Xuezhong L. Research on Enhancing Human Finger Vein Pattern Characteristics. Asia-Pacific Conference on Power Electronics and Design (APED), 2010.
22. Yang J, Shi Y. Finger-vein ROI localization and vein ridge enhancement. Pattern Recognition Letters. 2012; 33(12):1569–79.
23. Yang L., Yang G., Yin Y. and Zhou L. 2014. A Survey of Finger Vein Recognition. Chinese Conference on Biometric Recognition. 234-243.
24. Yilong Yin, Lu Yang, Gongping Yang and Lizhen Zhou. (2014), A survey of finger vein recognition. Shandong University publications, China.