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Integration of Palm and Fingerprint Features for Person Authentication Using Image Processing Techniques

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Abstract

In this paper we developed a biometric identification system that represents a valid alternative to conventional approaches. Nowadays, usage of biometric has been essential in everyday life. Biometric has been used in various fields like Visa card processing, military, medical treatment for authentication etc. The present system deals with multimodal biometric identification system based on palm print and fingerprint. The multimodal biometric that combines palmprint and fingerprint technology, which will provide better security and robustness comparing to the stand alone model have not been that much expanded. This paper provide an efficient palmprint and fingerprint technologies describing different pre-processing techniques, feature extraction and matching algorithms. Successively, the comparison of data base template and the input data is done with the help of Euclidean-distance matching algorithm. For palmprint recognition a novel approach of line feature extraction called Directional Line Energy Feature (DLEF) is used. Similarly for fingerprint recognition the methods called chain code and Radon transformation are applied. The combination of two biometric traits are collected and stored into database at the time of Enrollment. In the Authentication stage query images will be compared against the stored templates and match score is generated. The experimental results demonstrated that the proposed palmprint achieves a recognition accuracy of 92%, fingerprint of 90% and multimodal biometric system achieves a recognition accuracy of 87% , thus improving system accuracy and reliability.

Keywords: *Biometrics, palm print, Fingerprint, multimodal, Euclidean distance, neural network*

1. Introduction

In the recent years, biometric authentication has become popular in modern society. Multimodal biometric person authentication systems integrate multiple authentication techniques and are important for many security applications such as government, defense, surveillance and airport security. Biometrics is defined as the science of recognizing an individual based on his/her physical or behavioral property. As password or PIN can lost or forgotten, biometrics cannot be forgotten or lost and requires physical presence of the person to be authenticated. Thus personal authentication systems using biometrics are more reliable, convenient and efficient than the traditional identification methods. Multimodal biometrics has become increasingly important, particularly because single modal biometrics has reached its bottleneck such as font and align. Multimodal biometrics gives supplementary information between different modalities that increases recognition performance in term of accuracy and ability to overcome the drawbacks of single biometrics. Biometric authentication refers to the technology for personal identification or authentication based on our physiological (face, fingerprint and palm print) and behavioral characteristics (signature, gait and voice recognition). In this paper we concentrate on the physiological features such as fingerprint recognition and palm print recognition.

The palm print, as a relatively new biometric feature [1], has several advantages compared with other currently available features [2]. palm print contain more information than fingerprint, so they are more distinctive; palm print capture devices are much cheaper than iris devices; palm prints also contain additional distinctive features such as principal lines and wrinkles, which can be extracted from low-resolution images; a highly accurate biometrics system can be built by combining all features of palms, such as palm geometry, ridge and valley features, and principal lines and wrinkles, etc. It is for these reasons that palm print recognition has recently attracted an increasing amount of attention from researchers [3-7]. Zhang et al proposed to use a palm print as a biometric feature for identity recognition and obtained good results in offline palm print verification.

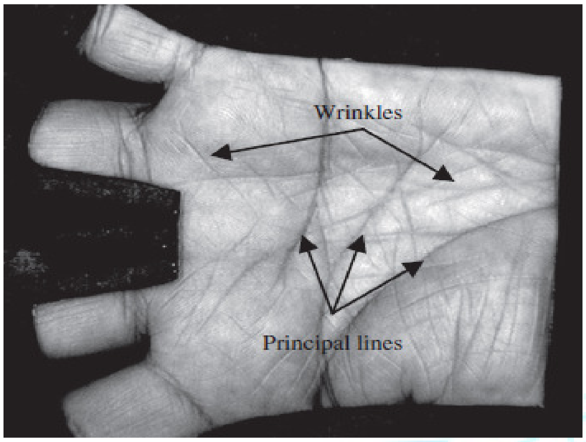

Fig.1 Structure of palm print

Finger print matching is minutia-based, which establishes the minutiae correspondences between two fingerprints.
A fingerprint is a pattern of ridges and valleys on the surface of a finger. It has been used for individual identification for legal purposes. Automatic fingerprint identification, which is established in modern information technology, is even applied to civilian purposes such as access control, financial security, and verification of firearm purchasers. In fact, the Automatic Fingerprint Identification Systems (AFISs) have performed well for years in controllable circumstances.

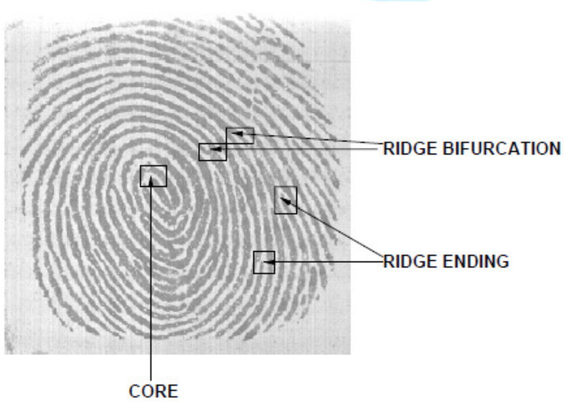

Fig.2 A fingerprint image with the core and four minutiae points marked on it.

The uniqueness of a fingerprint is determined by the topographic relief of its ridge structure and the presence of certain ridge anomalies termed as minutiae points (Fig.2). Typically, the global configuration defined by the ridge structure is used to determine the class[10,11] of the fingerprint, while the distribution of minutiae points is used to match and establish the similarity between two fingerprints[12,13]. Automatic fingerprint identification systems, that match a query print against a large database of prints (which can consist of millions of prints), rely on the pattern of ridges in the query image to narrow their search in the database (fingerprint indexing) and on the minutiae points to determine an exact match (fingerprint matching). The ridge flow pattern is seldom used for matching fingerprints.

2. Literature survey

John Christopher , Dr.T.Jabarajan (2010) has developed a multimodal biometric recognition system integrating palm print and fingerprint based on feature extraction fusion. The feature vectors are extracted independently from the pre-processed images of palm print and fingerprint. The proposed multimodal biometric system overcomes the limitations of individual biometric systems and also meets the response time as well as the accuracy requirements.

Ephin M, Shreya Mohan, N. A. Vasanthi (2009) has presented a survey on palm print and fingerprint has been investigated over many years. The multimodal biometric that combines palm print and fingerprint technology, which will provide better security and robustness comparing to the stand alone model have not been that much expanded. Finally some suggestions are also provided based on the theoretical study.

Mitul D Dhameliya, Jitendra P Chaudhari (2013) has suggested a basic aim of a biometric system is automatically discriminate between subjects as well as protect data. It also protects resources access from unauthorized users. We develop a biometric identification system that represents a valid alternative to conventional approaches. The experimental results demonstrated that the proposed multimodal biometric system achieves a recognition accuracy of 87% Multimodal biometric system provides optimal False Acceptance Rate (FAR) & False Rejection Rate (FRR), thus improving system accuracy & reliability.

Anil K.Jain, Jianjian Feng, Karthik Nandakumar (2010) has presented the fingerprint matching that has been successfully used by law enforcement for more than a century. The technology is now finding many other applications such as identity management and access control. They describe an automated fingerprint recognition system and identify key challenges and research opportunities in the field.

Sargur N. Srihari and Harish Srinivasan (2008) has given the context of automatic fingerprint verification the task consists of three steps: feature extraction, where features (typically minutiae) are extracted from each fingerprint, scoring, where the degree of match between the

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two sets of features is determined, and decision, where the score is used to accept or reject the hypothesis that the input and template belong to the same individual. The performances of the likelihood and ROC methods are compared for varying numbers of minutiae points available for verification.

Adams Kong, David Zhang, Mohamed Kamel (2009) has proposed a Palm print recognition that has been investigated over 10 years. During this period, many different problems related to palm print recognition have been addressed. And provides an overview of current palm- print research, describing in particular capture devices, preprocessing, verification algorithms, palm print- related fusion, algorithms especially designed for real-time palm print identification in large databases and measures for protecting palm print systems and users' privacy.

Lei Zhang, Zhenhua Guo, Zhou Wang and David Zhang (2007) has presented a Palm print is a unique and reliable biometric characteristic with high usability. And propose a modified complex wavelet structural similarity index (CW-SSIM) to compute the matching score and hence identify the input Palm print .And experimental results show that the proposed scheme outperforms the state-of-the art methods by achieving a higher genuine acceptance rate and a lower false acceptance rate simultaneously.

Jianjiang Feng, zhengyu Ouyang, Anni Cai (2006) has developed fingerprint matching is minutia-based, which establishes the minutiae correspondences between two fingerprints and a novel fingerprint matching algorithm is presented, which establishes both the ridge correspondences and the minutia correspondences between two fingerprints. Preliminary results on FVC2002 databases show that ridge matching approach performs comparably with the minutia-based one.

Xiangqian Wu, Kuanquan Wang and David Zhang (2004) has proposed palm-lines, including the principal lines and wrinkles, can describe a palm print clearly. This paper presents a novel approach of line feature extraction for palm print recognition called the directional line energy feature (DLEF). Best results have been obtained when DLEFs with different directions were employed.

Arun Ross, Sarat Dass, Anil Jain (2005) has given the process of automatic fingerprint matching is affected by the nonlinear deformation introduced in the image during fingerprint sensing. Given several template impressions of a finger, we estimate the “average” deformation of each template impression by comparing it with the rest of the impressions of that finger. An index of deformation is proposed for choosing the deformation model with the least variability arising from a set of template impressions corresponding to a finger.

3. Proposed approach

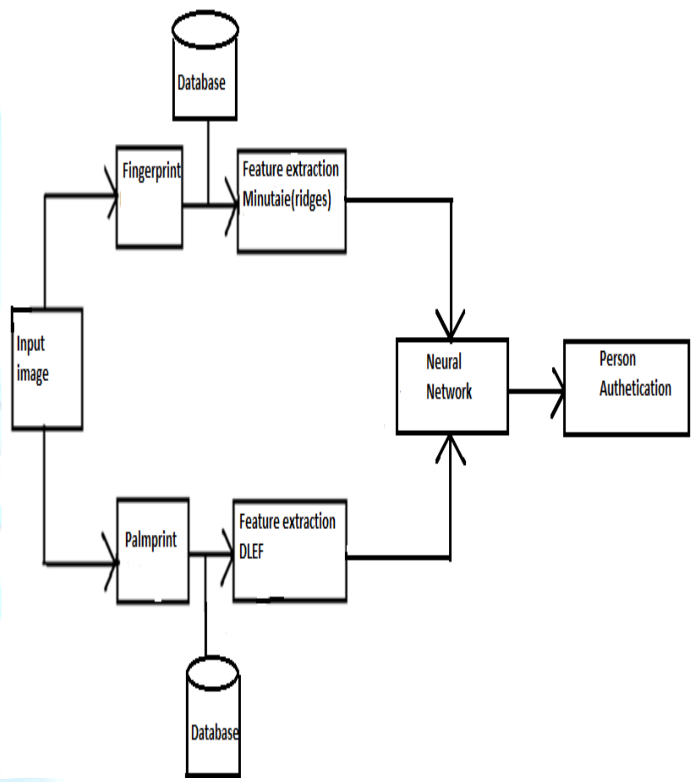

Fig.3 Proposed system

Our methodology for testing multimodal biometric systems focuses on the feature level fusion. This methodology has the benefit of exploiting more amount of information from each biometric.

Our work comprises of input image of palm and fingerprint, feature extraction like Directional line energy Feature for palm print and chain code and radon transform for fingerprint recognition. These features are fused and stored in a database as a parameter for finding the matched image from the database. The feature vectors are extracted independently from the pre-processed images of palm print and fingerprint. The feature vectors of input images are then compared with the templates of the database to produce the output. Combining more than one biometric modality progresses the recognition accuracy, reduces FAR and FRR and classifier used for palm print and fingerprint is neural network. The proposed multimodal biometric system overcomes the limitations of individual biometric systems and also meets the accuracy requirements.

3.1 Image Database

Palm print images are real images .and are taken from digital camera of 16 mega pixels.
As shown in below finger the principal lines are visible clearly. In this paper, we are concentrating only on principal lines that are dark lines which are shown in below figure.

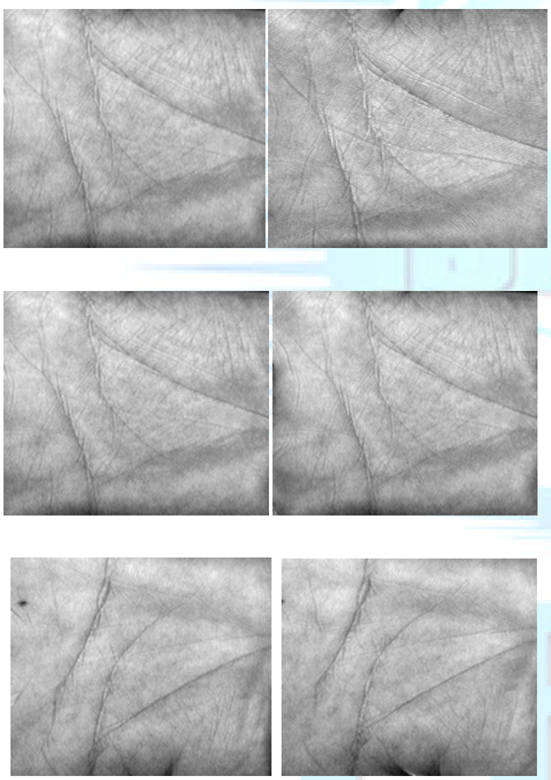

Fig.4 Samples of palm print images

In this work, fingerprint images are taken from Internet because the real fingerprint images are not clear and in fingerprint image, ridges and valleys are not visible clearly. In real images, it is not possible to see the gap between the lines so we took from internet.

Fig.5 samples of Fingerprint images

3.2. Pre-Processing

Pre-processing is carried out for palm print and fingerprint separately. After the image is captured by the scanner it may be distorted or blurred due to the bad environmental conditions. In these conditions a good pre-processing method is a must. The goal of fingerprint image pre-processing is to increase the clarity of the ridge structure so that minutiae points can be easily extracted. Low pass filters like Gaussian can be used for smoothening. In addition to Gaussian filter, chain code for minutiae image and Radon transform for virtual minutiae image are used. and is adopted to enhance fingerprint image quality. Sometimes the binarized fingerprint image contains a number of false minutiae. In [14] a detailed pre-processing is mentioned to remove false minutiae.

When palm prints are captured, the position, direction and stretching degree of a palm may vary from time to time. Therefore, even palm prints from the same palm may have a little rotation and shift. Furthermore, the sizes of palms are different from one another. Hence palm print images should be orientated and normalized before feature extraction and matching. The goal of palm print pre-processing is to increase the clarity of the image so that the principal lines can be easily extracted.

3.3 Feature extraction

3.3.1 Palm print feature extraction

We using one of the novel approach of line feature extraction for palm print recognition called the Directional

Line Energy Feature (DLEF). The directional lines in different directions are first extracted using a set of directional line detectors. Then each directional line magnitude image is divided into several overlapped small grids and the magnitudes of the line points in these grids are used to compute the DLEF.

Consider an input pre- processed palm print I, whose size is 128x128. Let $L_{\theta j} = (1 \leq j \leq k)$ be K directional line magnitude image of palm print I. First each $L_{\theta j}$ is divided equally into 25, or 5x5 blocks of 32X32 pixels, where each block overlaps 32x8=256 pixels of the each adjacent block. Then the directional line energy (DLE) of block in θ_j direction is defined as:

$$E_{\theta j}^{i} = \sum_{l=1}^{m} \{[L_{\theta j}(xl, yl)]^2 XR(xl, yl\}, 1 \leq i \leq 25 \quad (1)$$

Where m is the total number of points in block i; $(x1, y1), (x2, y2), \ldots\ldots (xm, ym)$ are the coordinates of the points.

A Kx5x5-dimensional vector is constructed for the whole palm print as:

$$V=(E_{\theta 1}^{1}, E_{\theta 1}^{2}, \ldots, E_{\theta 1}^{25}, \ldots, E_{\theta k}^{1}, E_{\theta k}^{2}, \ldots, E_{\theta k}^{25}) \quad (2)$$

This vector is normalized by using the maximum and minimum values of its components:

$$V1 = (e_{\theta 1}^{1}, e_{\theta 1}^{2}, \ldots e_{\theta 1}^{25}, \ldots, e_{\theta k}^{1}, e_{\theta k}^{2}, \ldots, e_{\theta k}^{25}) \quad (3)$$

$$e_{\theta j}^{i} = \frac{E_{\theta j}^{i} - E_{min}}{E_{max} - E_{min}}, 1 \leq i \leq 25, 1 \leq i \leq 25 \quad (4)$$

Where E_{max} and E_{min} are the maximum and minimum values of the components of V, respectively. The normalized vector V1 is called a directional line energy feature (DLEF) with K directions. Since $E_{\theta j}^{i}(e_{\theta j}^{i})$ reflects the strength of the palm-lines in block i in direction, θ_j DLEFs reflects the strength of the palm-lines in different directions at different spatial position on a palm.

3.3.2 Fingerprint Feature extraction

For extracting the features from the fingerprint image, a popular method is minutiae extraction. A fingerprint is made of a series of ridges and furrows on the surface of the finger. Minutiae extraction algorithm will find out the minute points from the fingerprint and then map their relative placement on the finger. When the fingerprint is of low quality, it will be difficult to extract the minutiae points. For that only we are using Gaussian filters and other image enhancement techniques at the pre-processing stage. The output of this algorithm will be the image template containing the minutiae details. There are two types of minutiae points. Ridge ending and Ridge bifurcation [15]. In [16] an advanced fingerprint feature extraction method is introduced through which minutiae are extracted directly from original gray-level fingerprint images without binarization and thinning. Chain code and radon transform can also be used to extract features from fingerprint [17] .

Radon Transform

The Radon transform represents an image as a collection of projections along various directions. It is widely used in areas ranging from seismology to computer vision.

The radon transform of an image f(x,y) , denoted as , $g(s, \theta)$ is defined as its line integral along a line inclined at an angle θ from the y-axis and at a distance s from the origin as shown in fig.6.

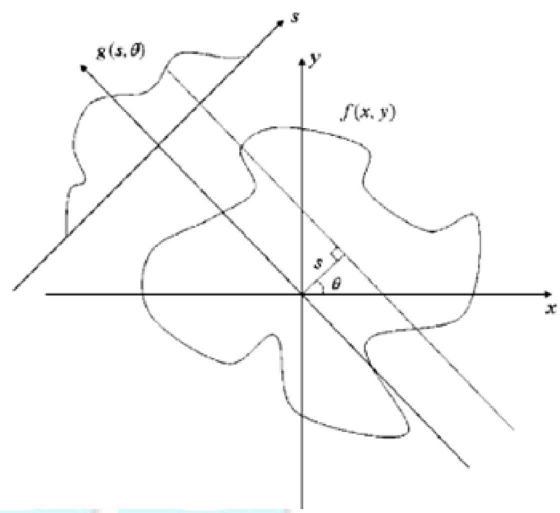

Fig.6 Projection integral in the directional θ

Mathematically, it is written as

$$g = (s, \theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(x\cos\theta + y\sin\theta - s) dxdy, \quad (1)$$

Where $-\infty < s < \infty, 0 \leq \theta \leq \pi$. The Radon transform $g(s, \theta)$ is the one-dimensional projection of f(x,y) at an angle θ .The Radon transform has the following useful properties for the affine transformations of an image.

(P1) Translation of an image by (x_0, y_0) causes the Radon transform to be translated in the direction of s; i.e.,

$$f(x - x_0, y - y_0) \leftrightarrow g(s - x_0\cos\theta - y_0\sin\theta, \theta) \qquad (2)$$

(P2) Scaling (retaining aspect ratio) of an image by a factor $\rho(\rho > 0)$ causes the Radon transform to be scaled through the same factor, i.e.,

$$f(\rho x - \rho y) \leftrightarrow \frac{1}{|\rho|} g(\rho s, \theta) \qquad (3)$$

(P3) Rotation of an image by an angle θ_r causes the Radon transform to be shifted by the same amount, i.e.,

$$f(x\cos\theta_r - y\sin\theta_r, x\sin\theta_r + y\cos\theta_r) \leftrightarrow g(s, \theta - \theta_r). \; (4)$$

Chain Code

The first step of the construction of the chain code is to extract the boundary of the image. Chains can the boundaries or contours of any discrete shape composed of regular cells. In the content of this work, the length *l* of each side of cells is considered equal to one. These chains represent closed boundaries. Thus, all chains are closed. Extracting the contour depends on the connectivity. In the content of this paper we use pixels with four-connectivity. The simplest contour following algorithms were presented by Papert and Duda and Hart. Thus using these algorithms it is possible to represent shape contours by only two states: left turn (represented by “1") and right turn (represented by “0"). The above mentioned process produces a chain composed of only binary elements.

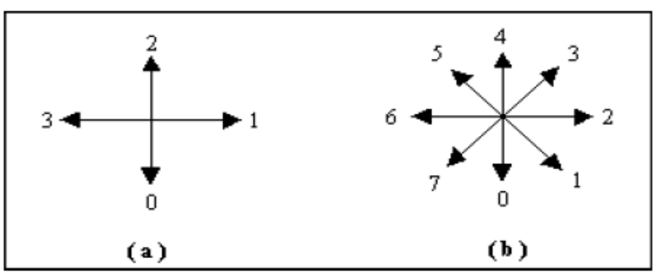

Fig.7 Directions of the neighbours :(a) 4 connected (b) 8 connected

In this paper we proposed a new algorithm to find the contour of a binary image and use this contour to obtain the chain code. Since we use pixels with 4-connectivity, the four neighbors of any point can be represented by directions as illustrated in figure7 (a). To find the contour of a binary image we apply the following algorithm:
Step 1. For all pixels with value 0 (black) in the image, set the pixel that has the direction 2 in 4-connected to 0.
Step 2. In the new image (i.e., image obtained from Step 1), also, for all pixels with value 0, set the pixel that has the direction 1 in 4-connected to 0.
Step 3. Remove the old pixels (in the original image) that have 8-connected as shown in figure 7(b).

Minutiae Extraction Using Chain code

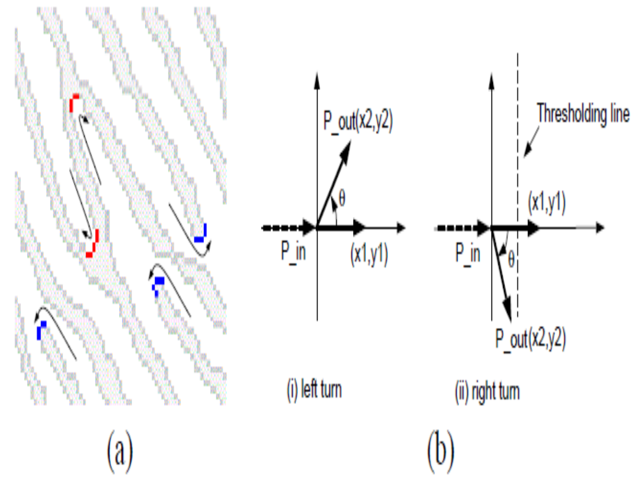

Fig.8 (a) Minutiae location in chain code contours, (b) the distance between the thresholding line and the y-axis gives a threshold for determining a significant turn

Most of the fingerprint minutiae extraction methods are thinning-based by which the skeletonization process converts each ridge contour to one pixel wide. The minutiae points are detected by tracing the thin ridge contours. When the trace stops, an end point is marked. Bifurcation points are those with more than two neighbors [18]. The alternate method of using chain coded contours is presented here. The direction field estimated from chain code gives the orientation of the ridges and information on any structural imperfections such as breaks in ridges, spurious ridges and holes. The standard deviation of the orientation distribution in a block is used to determine the quality of the ridges in that block .We consistently trace the ridge contours of the fingerprint images in a counter-clock-wise fashion. When we arrive at a point where we have to make a sharp left turn we mark a candidate for a ridge ending point. Similarly when we arrive at a sharp right turn, the turning location marks a bifurcation point (Figure 8 (a)).
To determine the significant left and right turning contour points from among the candidates marked during the trace, we compute vectors Pin leading in to the candidate point P from its several previous neighboring contour points and Pout going out of P to several subsequent contour points. These vectors are normalized and placed in a Cartesian coordinate system with Pin along the x-axis (Figure 8 (b)). The turning direction is determined by the sign of

S(Pin; Pout) = x1y2 - x2y1

S(Pin; Pout) > 0 indicates a left turn and S(Pin; Pout) < 0 indicates a right turn. A threshold T is then selected such that any significant turn satisfies the conditions:

x1y1 + x2y2 < T Since the threshold T is the x-coordinate of the thresholding line in Figure8 (b), it can be empirically determined to be a number close to zero. This ensures that the angle made by Pin and Pout is close to or less than 90°.

Delaunay Triangulation

A unique topological structure with the fingerprint minutiae called Delaunay triangulation. This allows for choosing more "meaningful" minutiae groups (i.e., triangles) during indexing, preserves index selectivity, reduces memory requirements without sacrificing recognition accuracy, and improves recognition time.

Triangulation is a process that takes a region of space and divides it into subregions. The space may be of any dimension, however, a 2D space is considered here since we are dealing with 2D points (minutiae). In this case, the subregions are simply triangles. Triangulation has many applications in finite elements simulation, surface approximation and nearest neighbor identification [16]. Here, however, our goal is to associate a 2D topological structure with the minutiae. Given a set *S* of points *p*1, *p*2, . . . , *PN*, we can compute the Delaunay triangulation of *S* by first computing its *Voronoi* diagram. The Voronoi diagram decomposes the 2D space into regions around each point such that all the points in the region around *pi* are closer to *pi* than they are to any other point in *S*. Given the Voronoi diagram, the Delaunay triangulation can be formed by connecting the centers of every pair of neighboring Voronoi regions. Figure a show a set of 2D points, their Voronoi diagram is shown in Figure 9b while their Delaunay triangulation is shown in Figure 9c.

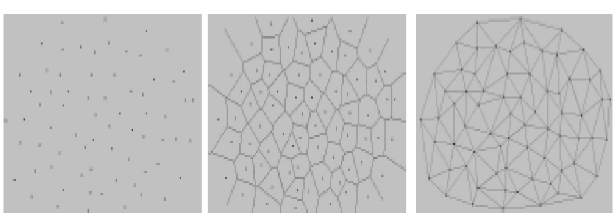

Fig.9 (a) A set of points, (b) its Voronoi diagram and (c) Delaunay Triangulation

3.4 Classification

3.4.1 Neural network

In this paper, neural network classifier is used for both palm print and Fingerprint recognition.

Neural network is formed in three layers, called the **input layer, hidden layer, and output layer**. Each layer consists of one or more **nodes**, represented in this diagram by the small circles. The lines between the nodes indicate the flow of information from one node to the next. In this particular type of neural network, the information flows only from the input to the output (that is, from left-to-right). Other types of neural networks have more intricate connections, such as feedback paths. The nodes of the input layer are **passive**, meaning they do not modify the data. They receive a single value on their input, and duplicate the value to their multiple outputs.

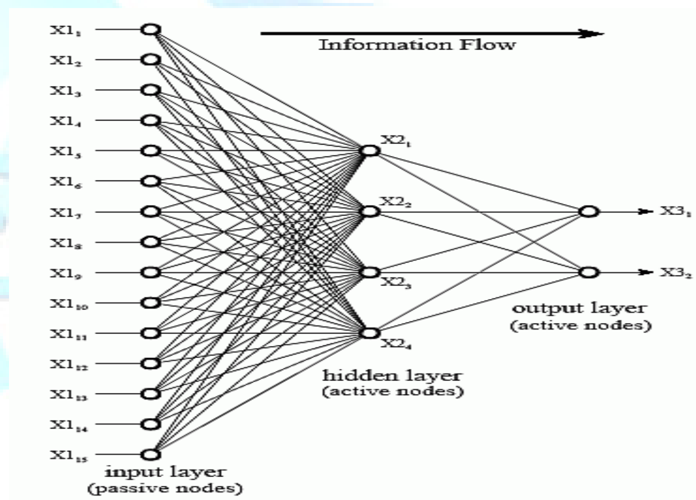

Fig.10 Neural network Architecture

Fig. shows the Neural network architecture. This is the most common structure for neural networks: three layers with full interconnection. The input layer nodes are passive, doing nothing but relaying the values from their single input to their multiple outputs. the nodes of the hidden and output layers are active. The action of this neural network is determined by the weights applied in the hidden and output nodes.

In the feed forward neural network, input layer consists of 4 features. and at the hidden layer there are 6 classes of both images. And one of the class is matched which is given as an output. Network is trained using sigmoid and pure linear function with an learning rate of 0.04. The goal is to set an error rate of 0.0001.

An epoch is just an iteration. an epoch is a measure of number of times all of the training vectors are used once to update the weights.

4. Result and Discussion

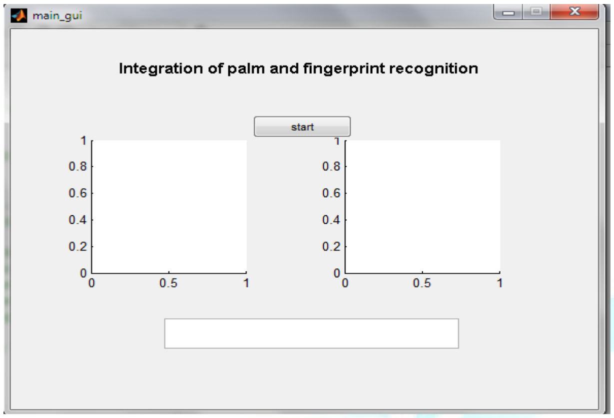

Fig .1

Fig.1. shows input screen to accept input image. The input image will be selected from the database.

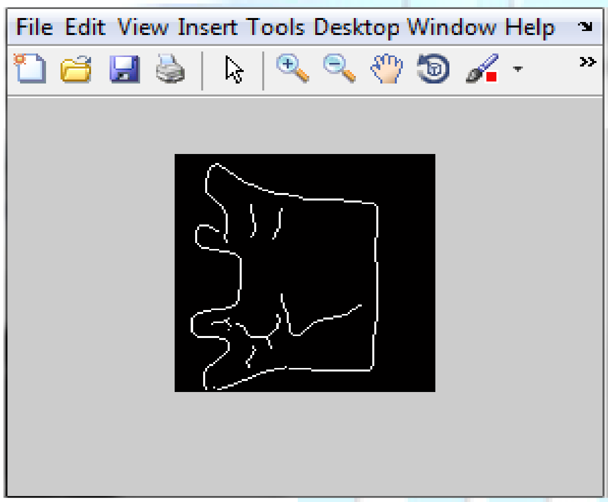

Fig.2

Fig.2. shows the edge orientation of input palm image. The basic idea is to find the gradiants of the image. In the above fig, it displays the Principal lines using Directional Line Energy feature (DLEF) as feature extraction. The Principal lines which help for recognition are extracted and trained by neural network classifier.

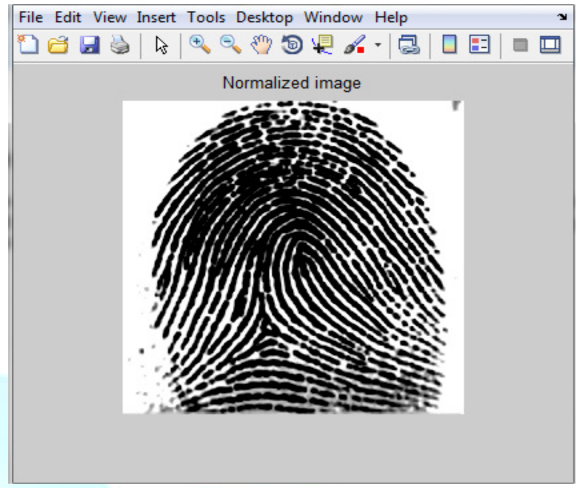

Fig.3

Above fig shows the Normalizition of the image. Which means the normalization is performed to remove the influence of the sense noise or distortion and gray-level deformation. And it preserves the clarity of the ridges and valleys structures.

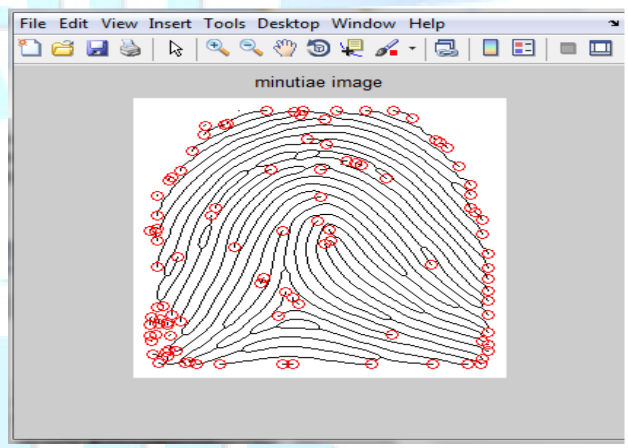

Fig.4

Fig.4. shows the minutiae image which means the specific point in the finger image.The red circles which are shown in-between the image are the minutiae. And here we used a method called chain code for identifying these minutiae.

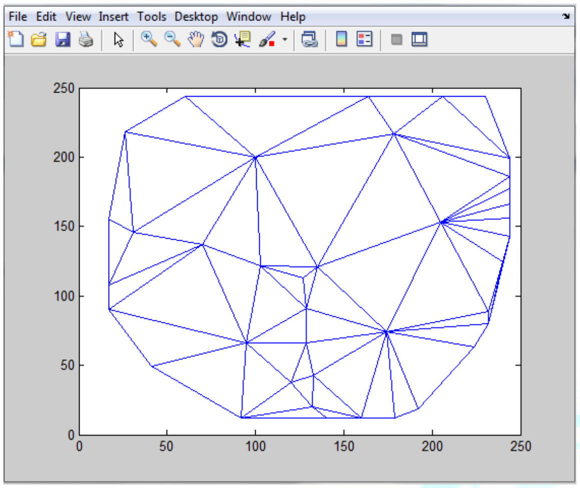

Fig.5

Fig.5. shows the Delaunay Triangulation image which means it allows for choosing more "meaningful"minutiae groups (i.e., triangles) during indexing, preserves index selectivity, reduces memory requirements without sacrificing recognition accuracy, and improves recognition time. We Computing the Delaunay triangulation *by* first computing its Voronoi diagram. The Voronoi diagram decomposes the 2D space into regions around each point.

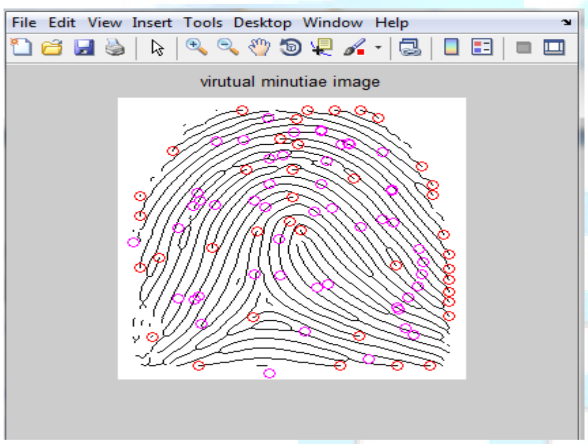

Fig.6

Fig.6. shows the virtual minutiae image .for this image we used one of the transformation called Radon transform for finding this virtual minutiae. The red circles are the real minutiae and the purple ones are virtual minutiae.

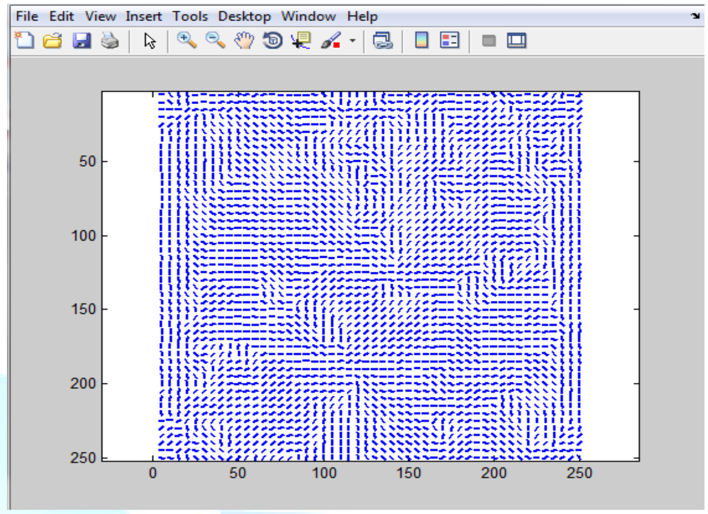

Fig.7

Fig.7. shows the chain code contours which means the minutiae points are detected by tracing the thin ridge contours. When the trace stops, an end point is marked. Bifurcation points are those with more than two neighbours. When we arrive at a point where we have to make a sharp left turn we mark a candidate for a ridge ending point. Similarly when we arrive at a sharp right turn, the turning location marks a bifurcation point.

Fig.8

Finally after training Palm and Fingerprint image, the Person recognised and authenticated.

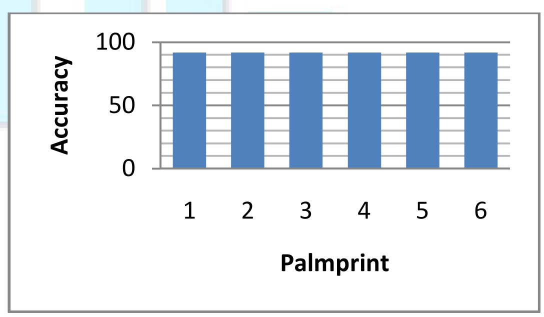

Fig.9. Percentage of accuracy of Palmprint

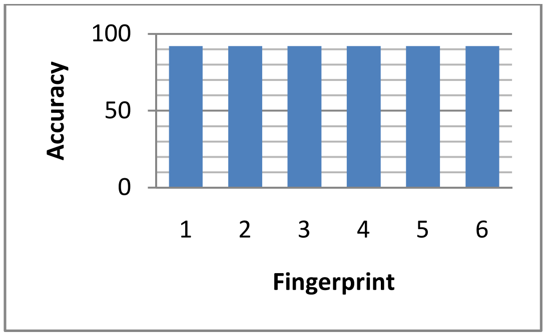

Fig.10.Percentage of accuracy of Fingerprint

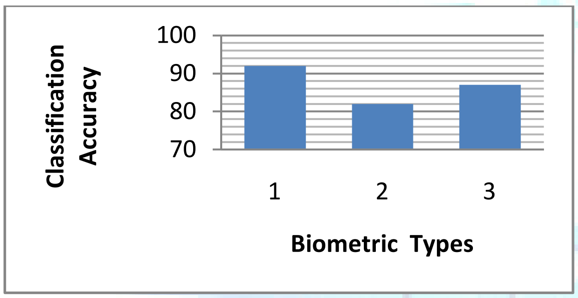

Fig.11.Combination of Palm and Fingerprint

5. Conclusion

Biometric systems are widely used to overcome the traditional methods of authentication. But the unimodal biometric system fails in case of biometric data for particular trait. Thus the individual score of two traits (palm print, fingerprint) are combined at classifier level and trait level to develop a multimodal biometric system. Multimodal system performs better as compared to unimodal biometrics with accuracy of more than 87%.

References

[1] D. Zhang, Automated Biometrics – Technologies and Systems, Kluwer Academic Publishers, 2000.

[2] A. Jain, A. Ross and S. Prabhakar, “An introduction to biometric recognition,” To appear in IEEE Transaction on Circuit and System for Video Technology, 2003.

[3] D. Zhang and W. Shu, “Two novel characteristics in palm print verification: datum point invariance and line feature matching,” Pattern Recognition, vol. 32, pp. 691-702, 1999.

[4] N. Duta, A. Jain and K.V. Mardia, “Matching of palm print,” Pattern Recognition Letters, vol. 23, no.4, pp. 477-485, 2001.

[5] D. Zhang, W. Kong, J. You and M. Wong, “Online palm print identification,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 9, pp. 1041-1050, 2003.

[6] C. C Han, H. L. Chen, C. L. Lin and K. C. Fan, “Personal authentication using palm-print features,” Pattern Recognition, vol. 36, no. 2, pp. 371-381, 2003.

[7] A. Kumar, D. C. M. Wong1, H. C. Shen1 and A. Jain, “Personal Verification using Palm print and Hand Geometry Biometric,” Lecture Notes in Computer Science, vol. 2688, pp. 668-678, 2003.

[8] M. Cannon, M. Byrne, D. Cotter, P. Sham, C. Larkin, E. O'Callaghan, Further evidence for anomalies in the hand-prints of patients with schizophrenia: a study of secondary creases, Schizophrenia Research 13 (1994) 179–184.

[9] A. Kong, D. Zhang, G. Lu, A study of identical twins palm print for personal verification, Pattern Recognition 39 (11) (2006) 2149–2156.

[10] K. Karu, A.K. Jain, Fingerprint classification, Pattern Recognition 29 (3) (1996) 389–404.

[11] A. Senior, A combination "fingerprint classifier, IEEE Trans. Pattern Anal. Mach. Intell. 23 (10) (2001) 1165–1174.

[12] A.K. Jain, L. Hong, R. Bolle, On-line fingerprint verification, IEEE Trans. Pattern Anal. Mach. Intell. 19 (4) (1997) 302–314.

[13] Z.M. KovQacs-Vajna, A fingerprint verification system based on triangular matching and dynamic time warping, IEEE Trans.Pattern Anal. Mach. Intell. 22 (11) (2000) 1266–1276.

[14] Zhao, F., Tang, X. 2007. Preprocessing and post processing for skeleton-based fingerprint minutiae extraction. Pattern Recognition 40 (2007) 1270 – 1281

[15] Deshpande, A., S., Patil, S., M., Lathi, R. 2012. A Multimodel Biometric Recognition System based on Fusion of Palm print Fingerprint and Face. International Journal of Electronics and Computer Science Engineering. ISSN-2277-1956.

[16] Zhao, F., Tang, X. 2007. Preprocessing and postprocessing for skeleton-based fingerprint minutiae extraction. Pattern Recognition, 40(4), 1270-1281.

[17] Jain, A. K., Prabhakar, S., Hong, L. 1999. A multichannel approach to fingerprint classification. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 21(4), 348-359.

[18] R.O. Duda and P.E. Hart. Pattern classification and scene analysis. Wiley, New York, 1973.

[19] S. Papert. Uses of technology to enhance education. Technical Report 298, AI Lab, MIT, 1973.

[20] Gayathri, R. Ramamoorthy, P. 2012. Fingerprint and palm print Recognition Approach based on Multiple Feature extraction. European Journal of scientific research. Vol 76, No 4.

[21] Deshpande, A., S., Patil, S., M., Lathi, R. 2012. A Multimodel Biometric Recognition System based on Fusion of Palm print Fingerprint and Face. International Journal of Electronics and Computer Science Engineering. ISSN-2277-1956.

[22] J. You, W.K. Kong, D. Zhang, K.H. Cheung, "On hierarchical palm print coding with multiple features for personal identification in large databases", IEEE Transactions on Circuits and Systems for Video Technology 14 (2) (2004) 234–243.