Enhanced Fuzzy Feature Match Algorithm for Mehndi Fingerprints

Ayesha Butalia, Shubhangi Ingali, Madhavi Kulkarni

Abstract: The performance of biometric system is degraded by the distortions occurred in finger print image acquisition. This paper focuses on nonlinear distortions occurred due to 'Mehndi / Heena drawn on the palm/fingers. The present invention is to detect and rectify such distortions using feedback paradigm. If image is of good quality, there is no need to renovate features. So, quality of whole image is checked by generating exponential similarity distribution. Quality of local region is checked by the ridge continuity map and ridge clarity map. Then, we check whether feedback is needed or not. The desired features such as ridge structure, minutiae point, orientation, etc. are renovated using feedback paradigm. Feedback is taken from top K matched template fingerprints registered in the database. Fuzzy logic handles uncertainties and imperfections in images. For matching, we have proposed the Enhanced Fuzzy Feature Match (EFFM) for estimating triangular feature set of distance between minutiae, orientation angle of minutiae, angle between the direction of minutiae points, angle between the interior bisector of triangle and the direction of minutiae, and a minutiae type. The proposed algorithm incorporates an additional parameter minutiae type that assists to improve accuracy of matching algorithm. The experimentation on 300 Mehndi fingerprints acquired using Secugen fingerprint scanner is conducted. The results positively support EEFM for its efficiency and reliability to handle distorted fingerprints matching.

***Keywords**: Orientation Field Estimation,False Acceptance,False Rejection Rate,Genuine Acceptance Rate,Fuzzy Feature Match,Cross Number*

*****

I. INTRODUCTION

Biometric authentication system is commonlyemployed in forensic science to aid criminal investigations,e-commerce, and electronic personal ID cards, etc. For user identification, biometric is most commonly used due to its unique, persistent and intrinsic physiological and behavioral features. Fingerprints are ridge and valley patterns on the tip of a human finger(Maltoni et al., 2009). However, designing the algorithms to extract salient features from fingerprints and match these features in a robust way are exigent problems. Fingerprint acquisition is very important step in fingerprint matching. Because nonlinear distortions are interleaved in fingerprint images during its acquisition.Distorted fingerprints contain imperfect information or noise, which mortifies the fingerprint matching performance and accuracy both. One way to deal with the distortion is to advance fingerprint image acquisition or registration system. Few present systems use scanners having video capturing capacity which needs extra memory. Two types of distortions are occurred in fingerprint image acquisition: photometric and geometric. Sensor noise and complex image background cause photometric distortions. Skin distortion such as elasticity of the skin, contact pressure, finger displacement, skin moisture content, imaging methods cause geometric distortions(Xuanbin Si et. al. 2015). Various algorithms have been designed by many researchers to covenant with these distortions. Many researchers focused on image acquisition step in biometric system. To deal with distortions, few researchers suggested using scanner with video capturing capability. But the loophole in such systems is the need of more memory to save videos and also the cost.

In India, women mostly draw *Mehndi* on fingers. When *Mehndi*is drawn on fingers, it adds a layer on skin of fingers which makes changes in the structure of ridges and valleys. It leads to the isometric distortions. Such distortions considerably reduce the matching performance of existing systems. And it becomes difficult to capture the desired features during image acquisition. If *Mehndi*is coloured dark, scanners cannot scan fingerprints images properly. In few regions, layer may be expanded or contracted. As a layer is added on skin, the distance between ridges gets amended(Ingale et. al. 2015). So, it becomes very critical to extract the desired features and perform matching of template and query images. Hence, a multispectral fingerprint scanner is used for such fingerprints, which is able to acquire subsurface features as well as surface feature even in poor conditions. Acquired fingerprint images are of squat quality as shown in Fig. 1. Hence, to extract real features from the query image, it becomes essential to enhance a squat quality fingerprint image. Extracting essential features from geometrically distorted fingerprint images is the most challenging problem.

Fig. 1. A squat quality fingerprint image

A fingerprint is an exclusive prototype of ridges and valleys on the surface of a finger of an individual(Xiaoguang et al, 2007). Orientation field and minutiae are the most observant and consistent discriminating features. Distortions in the acquired image consequences in fictitious minutiae points or amputation of genuine ones, thus directly influence the performance of algorithms to unfailingly match the fingerprints. Hence, it has become a tricky predicament to develop a novel approach to enhance the fingerprint matching performance of distorted images.

In the proposed system, we make use of single image of fingerprint. Feature extraction means the orientation field estimation and minutiae extraction is a decisive footstep in fingerprint matching. Because orientation field and minutiae are the feature vectors used in fingerprint matching. The features of the distorted fingerprint are renovated using feedback paradigm from exemplar fingerprints. Feedback paradigm assists to upgrade a quality of orientation field, which in turn escorts to improve an accuracy of fingerprint matching algorithm. If the query image is of good quality, then there is no need of feedback.There are many existing approaches implemented to renovate the features of the fingerprint images. But these approaches consume time in training those systems. Training dataset must be of good quality. So, the renovation of features depends on the training dataset. Here to take a feedback we consider the registered images only and we ensurethat whether feedback is indeed needed by verifying the quality of image.

Fig. 2 illustrated the data flow in the proposed system. Initially, preprocessing, the feature extraction and matching is done in "bottom up" fashion.Feedback computation is implemented in "top-down" fashion. Fuzzy set theory deals with an uncertainty efficiently(L.A. Zadeh 1965, G.J. Klir, et al, 1997). In the proposed enhanced fuzzy feature matching *(EFFM)* algorithm, a triangular feature vector is used to estimate the similarity score between query and template fingerprint. A triangular feature vector constitutes the distance between two minutiae points, the angle between direction and orientation angle, the angle between the orientation of minutiae with the direction of the interior angle bisector of corner. Here, we select a first pair of matching triangle and then next attached one. Area of overlapping region is used to measure the similarity between two fingerprints. While matching the distorted fingerprints, the system may give following result:

a) Distorted fingerprint truly matches with its pair.
b) Erroneously matches with the false fingerprint.
c) Erroneously discards the true match.
d) Erroneously matched with false match.

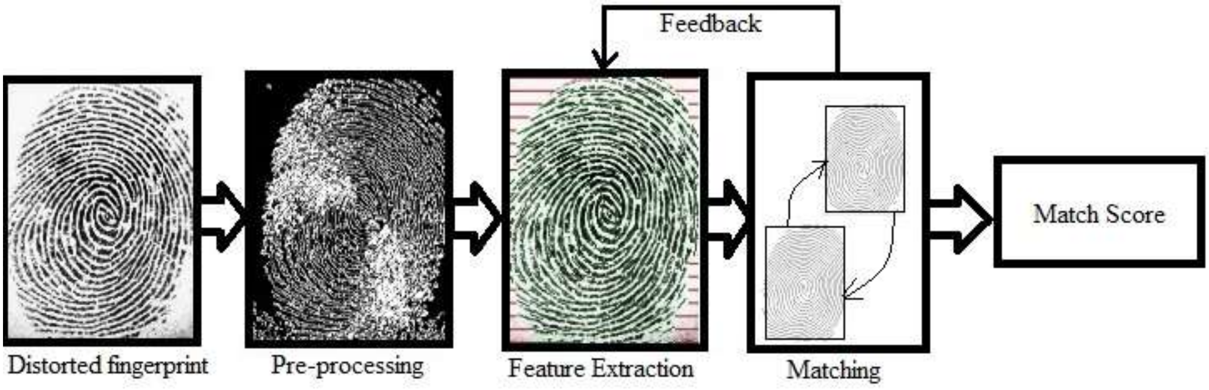

Fig. 2. Illustrating the data flow in the distorted fingerprint matching system

The objectives of the proposed system are:1) to improve the genuine acceptance rate(GAR) of the biometric sytems, 2)minimize the false acceptance rate(FAR) as well as the false rejection rate(FRR) of the biometric system, 3) reduce the dependency on training dataset., 4) to accept a single image as an input to handle distortions and 5) to remove the loopholes of existing biometric systems. To achieve these objectives, we proposed to use feedback paradigm to deal with distortions in the query fingerprint images. The rest of the paper is organized as follows: Section 2 presents related work done by various researchers andvarious approaches to restructure an orientation map and fingerprint matching. Section 3 presents the proposed method based on ridge orientation and minutiae points information. Section 4 presents result analysis of proposed system. Section 5 presents conclusions and future work.

II. RELATED WORK

This section illustrates the work done by various researchers in improving the performance of biometric systems. Dealing with the nonlinear distortions has become a decisive dilemma. In order to deal with distortions, authors proposed a technique to measure the forces and torques on the scanner directly and prevent capture when an excessive force is applied. Obviously, this technique requires a specialized hardware to measure the forces at capture time(N. K. Ratha et al., 1998).Chitra Dorai, Nalini Ratha, and Ruud Bolle suggested a method, which needs a video sequence of fingerprint images obtained to measure the distortion in input given to the scanner. When excessive distortion is seen, the print can be rejected and a new print requested(Chitra Dorai et al., 2000). Here, again there is ahardware requirement in the form of processor power, since the live video feed fromthe scanner needs to be processed to measure the distortion at the time of capture ifdistorted prints are to be rejected, then there is still an opportunity to capture anotherprint. Both methods can be used to choose the least distorted print from a capturesequence, though there are other criteria affecting the optimal choice of print, includingimage quality and area.

In normalized fuzzy similarity measure (NFSM), local topological structure is used for alignment and also to compute resemblance between the template and input fingerprints(Xinjian et al., 2006).R. Kavitha Jaba Malar et al proposed an algorithm based on a controlled triangle feature set inscribed in a rhombus tomatch the deformed fingerprints(R. Kavitha Jaba Malar et al., 2014).Authors proposed a scheme for fingerprint matching based on all-inclusive minutia and the binary relation between minutiae. Here, a graph is used to represent a fingerprint. The vertex set consists of the all-inclusive minutiae and the edge set consists of the local binary minutia relations. Then, from the binary relation, the transformation-invariant and transformation variant features are extorted. The local matching probability is estimated by using the transformation-invariant features, whereas the fingerprint rotation transformation with the adaptive Parzen window is modeled by using the transformation-variant features. Parzen window shows the periodic property with more accuracy in the similarity of local structural pairs. Here, the probability density curve shows the probable capability of fast impostor rejection(Xiaoguanget al.,2007).

To deal with non-linear distorted fingerprints, Nguyen Thi Huong Thuy suggested a warping technique for a fingerprint matching based on local Thin-Plate-Spline (TPS) deformation model. An affine transformation is used to determine the set of corresponding minutiae pairs between two fingerprints. By comparing their local ridge-valley structure, a set of corresponding pseudo-minutiae pairs are formed. In order to locate next analogous minutiae pairs, these minutiae are related with the identified analogous minutiae pairs to pick a appropriate signpost minutiae set for Local Thin Plate Spline deformation model in nine partial regions of fingerprint images. This procedure is repeated until no more new corresponding minutiae pairs are distinguished or the number of corresponding point pairs is large enough(Nguyen Thi et al., 2013). To deal with the problem of fingerprint alteration, authors described a distorted fingerprint detection and rectification algorithm. Distortion is detected using the ridge orientation map and period map of a fingerprint are as the feature vector. A SVM classifier is trained to distinguish the query fingerprint as distorted or normal. A nearest neighbor regression approach is considered to predict the distortion field from the query distorted fingerprint. The inverse of the distortion field is applied to renovate the distorted fingerprint into a normal one. But this approach does not support rolled fingerprints(Soweon Yoon et al, 2012, Xuanbin Si et al., 2015).

ACO algorithm is also proposed to handle a large distorted fingerprint matching. Minutiae similarities are measured by their orientation descriptor and local minutiae structure are input features to measure correspondence. An assignment graph is constructed by using a local minutia matching. The artificial ants use this graph and pseudo random proportional rules to find all minutiae correspondences. But it does not support non-linear distorted fingerprint images(Kai Cao et al., 2012). Few researchers started using ridge features along with minutiae to improve the accuracy of matching algorithms. The ridge features like ridge count, ridge length, ridge curvature direction, and ridge type depict the association between the minutiae. By using combined features of ridge and minutiae, minutiae are traversed in breadth first search manner to identify the analogous minutiae pairs. But this algorithm could not work well for fingerprint images with small foreground are and poor quality images and does not use global knowledge of fingerprints (Heeseunget al., 2011). Descriptor-based Hough transform is used to align fingerprints and computes resemblance between fingerprints by taking into account both minutiae and orientation field. As this algorithm depends only on manually marked minutiae, it cannot support the latent and rolled prints which are deficient in desired features(Alessandraet al., 2013).

Later on many researchers started focusing the reconstruction of desired features of fingerprint images such orientation field, etc. Dictionary based approach is also explained by few researchers, in which a prior knowledge about fingerprint patterns is represented in dictionaries.The use of only a global dictionary has a hitch that a legitimate local ridge patterns may appear at anunfeasible location of fingerprint. This problem is equivalent to real word error in spelling correction(Jianjiang et al, 2013). Xiao Yang et al proposed a methodology to rectify orientation field based on localized dictionaries (Xiao Yang et al, 2014).Two types of dictionaries are used: orientation patch dictionary and ridge structure dictionary. Here, the orientation patch dictionary is considered to modify the initial orientation field in the input region of interest. The ridge structure dictionary is considered for region of interest segmentation and enhancement(Anil K. Jainet al.,). Authors designed an approach in which two dictionaries: orientation patch dictionary to restructure orientation patch and continuous phase patch dictionary to restructure the ridge pattern are constructed. Only the local orientation pattern is used for orientation field reconstruction. The ridge orientation reconstruction can be enhanced by using a prior knowledge of global orientation and remarkable points. A rigid ridge frequency is used. but this method cannot restructure the field of ridge frequency directly by using the minutiae position and direction(Kai Cao et al ., 2014).

Dictionary based approaches have some pitfall: (1) the initial set of orientation field used to construct orientation patch dictionary itself is nottrustworthy, (2) adding more features like ridge results in large patch size, which extra memory. Thus, it reduces their efficiency, (3) the dictionaries are initially constructed from high quality fingerprints, which may not work well on squat quality latents. A ConvNet based approach using convolutional network is proposed to renovate latent orientation field(Kai Cao et al.,2015).The acquired image is enhanced using Short Time Fourier Transform (STFT). Initially, the fingerprint image is enhanced using STFT. The complex filter is used tolocate the core point from the enhanced image. The ROI is extracted based on thecore point which is centered at the enhanced image. A set of invariant moment featuresare extracted from partitioned sub-images of an ROI. Two measures: absolute distanceand BPNN are implemented for fingerprint matching. The maximum, minimum andaverage elements of the vectors of input fingerprint, template fingerprint and the differencevectors of them are provided as inputs to BPNN(M. Sadhana et al., 2015). Further, Sadhana M. et al developed fuzzy back propagation neural network to match fingerprints(Pooja Naval et al., 2014).

Prior art:

Distortion of fingerprint is one of the important factors resulting in a false non-match, which may cause a bad effect on fingerprint applications, especially on a personal identification. Two types of distortions are occurred in fingerprint image acquisition: photometric and geometric. Sensor noise and complex image background cause photometric distortions. Skin distortion such as elasticity of the skin, contact pressure, finger displacement, skin moisture content, imaging methods cause geometric distortions. Disadvantage of existing art is: a) it requires video as an input, which needs extra memory to store these videos. b) Distortion detection is dependent on training dataset. If training dataset is of poor quality, it degrades the performance of SVM classifier. c) Training SVM classifier consumes time.

US 7660447 B2 discloses detection of fingerprint distortion by deformation of elastic film or displacement of transparent board. A fingerprint matching apparatus includes a fingerprint distortion detection unit for detecting whether or not a correlation object intentionally distorts the finger put on the fingerprint reading face by, for example, applying excessively large force to the finger, or dragging or rolling the finger. With this configuration, it is possible to prevent a distorted fingerprint image from flowing into the fingerprint matching apparatus and therefore the probability of accurate fingerprint correlation can be increased.

US 7433500 B2 discloses method for recognizing digital fingerprints by distortion and computer system for using said method. A digital fingerprint recognition method providing the steps of activating an image distortion software program on a computer, displaying a digital fingerprint image on a screen of the computer in a presentation environment for the image distortion software, and distorting the digital fingerprint image so as to correct a fault in the fingerprint detected on the digital fingerprint image. The computer system having a man/machine interface, a processing unit that is used to analyze a digital fingerprint image, coupler for accessing one or more files containing at least one digital fingerprint image and an image distortion software program that is used to display a digital fingerprint image on the man/machine interface and to distort the digital fingerprint image by the man/machine interface.

WO 2015176411 A1 discloses method and system for rectifying distorted fingerprint. A method and a system for rectifying a distorted fingerprint are provided. The method includes: extracting a feature of a distorted fingerprint; searching for a reference distorted fingerprint whose feature is matched with the feature of the distorted fingerprint in a reference distorted fingerprint database; obtaining a dense distortion field of the reference distorted fingerprint in the reference distorted fingerprint database, and rectifying the distorted fingerprint to a normal one according to the dense distortion field of the reference distorted fingerprint.

US 6657185 B2 describes pattern detector for capturing images with reduced distortion. An irregular pattern detector includes a first optical system, a transparent light guide body and a second optical system. The first optical system has a light source. The transparent light guide body has an incident face receiving incident light from the light source of the first optical system, a detection face facing the incident face for placing of a subject having an irregular pattern, a curved surface reflecting scattered light from the detection face, an optical absorbing face facing the curved surface and having an opening outputting light reflected from the curved surface. The second optical system, such as an imaging lens, guides the light from the opening of the optical absorbing face of the transparent light guide body to a camera device. This irregular pattern detector can be scaled down, and can produce precise images without any deformation.

US 7054470 B2 discloses system and method for distortion characterization in fingerprint and palm-print image sequences and using this distortion as a behavioral biometrics. This invention uses a novel biometrics, called resultant fingerprints and palm-prints, for authentication. The novel biometrics are consecutive traditional print images where the subject physically changes the appearance of the print images by rotating or rotating and translating, or rotating, translating, and shearing the finger or palm. That is, it is a sequence of finger or palm-print images over a short interval of time where the images are modified according to the rotation or a combination of rotation and translation or a combination of rotation, translation, and shear. The rotational and translational and shear components of the motion in the sequence of print images are determined from the image-to-image flow. This flow is either computed from motion-compensation vectors of the sequence compressed in MPEG formats or directly from the uncompressed images. The global image-to-image flow is expressed in terms of an affine transformation, computed from the local flow in blocks around a non-moving central region. The rotational and translational components of this affine transformation are smoothed over a temporal neighborhood resulting in a function of time. This function of time is a behavioral biometrics which can be changed by the user when compromised. Matching of this function for authentication purposes is

ISSN: 2454-4248
188 – 197

achieved very much as is done in legacy signature matching authentication systems where two temporal signals are compared.

US 20080123909 A1 discloses a method of transforming minutiae using the Taylor series for interoperable fingerprint recognition between disparate fingerprint sensors, which parses the fields of a Standard Interchange Format (SIF) template having the level of minutiae proposed in SC37, extract information fields corresponding to resolution, image size, and minutiae, corrects the locations of minutiae constituting the template, and standardizes the minutiae, thus increasing a recognition rate for fingerprint matching, and which applies transformation parameters using the Taylor series to a golden template that is generated using a plurality of samples for the same fingerprint which are input from a plurality of disparate fingerprint recognition sensors, thus improving recognition performance and reliability of matching between the disparate sensors that use the transformation of minutiae merely by correcting the locations of the minutiae, without correcting resolution or distortion characteristics. In the minutiae transformation method, a golden template, which is a template including visible minutiae, is created. Transformation parameters are calculated using the Taylor series. A location of minutiae data calculated from the SIF templates is corrected using the transformation parameters.

US 6064753 A discloses system and method for distortion control in live-scan inkless fingerprint images. A computer system and method determines the force and/or torque applied during the image acquisition stage of a biometric characteristic. Images with very high or very low pressure or high shear torque are rejected and user/operator is notified to re-acquire the image. Alternatively, the application of force and torque by the subject is restricted mechanically so that the images are acquired while the force and/or torque are within acceptable ranges.

Indian women mostly apply ‘*Mehndi*/ Heena’ on palm, which colors dark and adds a layer on a skin of fingerprints. It becomes tricky task to extract the desired features from fingerprints. Due to a dark colored layer on skin, scanners cannot capture fingerprints properly. Also, the ridge structure is either expanded in few regions or contracted and it leads to change in the distance between the ridges. Now a day, distortion detection and rectification has become critical topic of researchers. Many methods have been invented, but few need video as an input.

Thus there is need to develop a method and system for detecting distortion and image authentication of fingerprints and also required to overcome the disadvantages of the existing method and system. Hence the present invention develops distortion detection and rectification system in fingerprint images using feedback paradigm.

III. ENHANCED FUZZY FEATURE MATCH*(EFFM)*

Matching fingerprint images with *Mehndi*is an exigent dilemma as these images are of squat quality and deficient in desired features. To upgrade the performance of fingerprint recognition system, different methods are adopted which are hardware based or statistical feature based. In hardware based techniques, few existing systems need scanners having video capturing capacity and high resolution. As video consists of multiple frames, existing approaches use it for distortion detection. In this project, we try to focus a distortion detection based on single image.It has become an essential and decisivepoint of research todevelop a new approach to surmount this problem.

We have listed major objectives that signified as motivation for the design of *EFFM*, they are as follows:

- Primary object of the present invention is to provide a system for distortion detection and rectification in fingerprint images using feedback paradigm.
- Another object of the present invention is to providea biometric authentication system to upgrade the matching performance by using a feedback paradigm.
- Yet another object of the present invention is to improve the false rejection rate as well as genuine acceptance rate.
- Yet another object of the present invention is to minimize the false acceptance rate.
- Yet another object of the present invention is to reduce the dependency on training dataset for the renovation of critical features.
- Yet another object of the present invention is to handle geometrical distortions occurred during image acquisition.
- Yet another object of the present invention is to check the quality of whole image by computing an exponential distribution of similarity.
- Yet another object of the present invention is to check the quality of local region by the ridge continuity map and the ridge clarity map.
- Yet another object of the present invention is torenovate the desired features such as ridge structure, minutiae point, orientation, etc. using feedback paradigm.
- Yet another object of the present invention is to help to improve accuracy of matching algorithm.

Fuzzylogic is best to tackle uncertainties and imperfection inan image.Distorted Fingerprint images consist of many uncertainties due to its squat quality. Hence, we proposed to use fuzzy logic(Shubhangi et. al. 2015). Then, the reconstruction of desired features is done by using feedback from top *K*exemplars having a high similarity score. Hence, feedback paradigm computation is very important step in our system. After, reconstruction of the legitimate features, similarity score is recomputed to find the genuine matching pair.

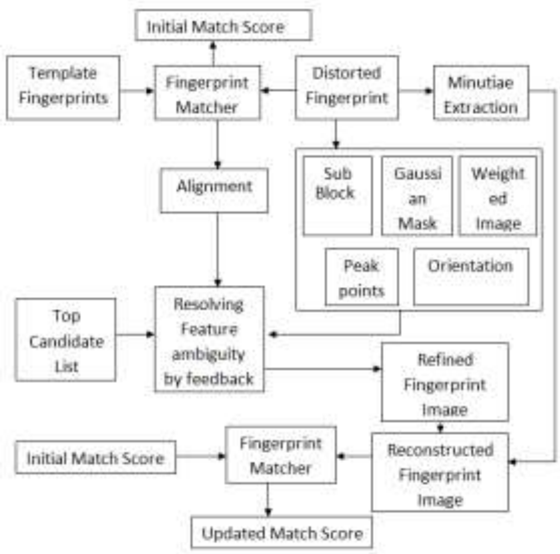

Fig. 2. System Overview

1.1. Image Acquisition and pre-processing

As scanner use rays and sensor suraface to scan the fingerprint, many scanners cannot capture a fingerprint with dark colored *Mehndi*. In this system, we used SecuGen scanner to acquire input fingerprint images from the user. As we are working on distortion occurred due to dark colored *Mehndi*, we used fingerprint images which are directly taken from the user. Aluminosity method is implemented to convert a raw fingerprint image to gray scale image.To distribute themost frequent intensities values among pixels, local histogram equalization technique is used(Muna F. et. al. 2011). We executed the binarization process using an adaptivethresholding(T. Romen Singh et. al. 2011). Thinning is done to purgeredundant pixels of ridges till ridges arejust a single pixel wide.

1.2. Minutiae Extraction and Orientation Field Estimation

Minutiae are the points at the ridge endings and theridge bifurcation(Roli et. al. 2011). To extract minutiae from fingerprint images, we implemented Rutovitz's crossing number(CN) method(M. James et. al. 2013). Here, we find out the type of minutiae: ridge ending point, continuing ridge point, crossing point and bifurcation point.The position of minutiae, the orientation angle and the type are the desired parameters of each minutia.

Local Fourier domain is used for orientation field estimation. Input fingerprint image is partitioned into 16X16 size sub-blocks. Smoothening of sub-blocks is done by using Gaussian filter with σ=16. To find magnitude spectrum, Fast Fourier transform(FFT) is applied on sub-blocks. Let (x, y) be peak minutiae point and calculate it's orientation(O(x, y)) and ridge frequencyvaluesf(x, y) as follows:

$$O(x,y) = \arctan\left(\frac{x}{y}\right) \quad (1)$$

$$f(x,y) = \frac{\sqrt{(x^2+y^2)}}{16} \quad (2)$$

Fig.3. Orientation of point(x,y)

Find out the difference orientation and ridge frequency of query and template fingerprint images, respectively. If the difference is minimum, then utilize these features for the reconstruction of the orientation and ridge frequency of query image(Sunpreet S. et. al. 2014).

1.3. Triangular Feature Set Construction

In fuzzy feature match (FFM), similarity between the triangular features of query and template fingerprints is used to computethe similarity(Xinjian Chen et. al. 2006).But additionally, we are also considering a type of minutiae. The feature vector of each triangle is build consisting of edge distance between minutiae, theangle between the direction from minutiae, the orientation differences within the region of minutiae and the angle between the orientation of minutiae with the direction of theinterior angle bisector and also a minutiae type. The feature vector of each triangleis represented as:

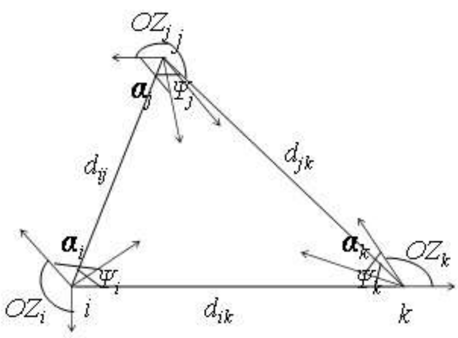

Fig. 4. Triangular Feature

$$FT_K = \{D_{ij}, D_{jk}, D_{ik}, \Psi_i, \Psi_j, \Psi_k, OZ_i, OZ_j, OZ_k, \alpha_i, \alpha_j, \alpha_k, T_i, T_j, T_k\} \quad (3)$$

where,

D_{ij} = the distance between minutiae *i* and *j*,

Ψ_i =the angle between the direction from minutiae *i* to *j* and the direction from minutiae *i* to *j*,

OZ_i =the orientation differences within the region of minutiae *i*,

α_i = the angle between the orientation of minutiae with the direction of the interior angle bisector of corner[19].

T_i, $T_j$and T_k are the minutiae types of coordinates of triangle.

Let FT_I be a feature set of input fingerprint.

$$FT_I = \{D_{ij}, D_{jk}, D_{ik}, \Psi_i, \Psi_j, \Psi_k, OZ_i, OZ_j, OZ_k, \alpha_i, \alpha_j, \alpha_k, T_i, T_j, T_k\} \quad (4)$$

Let FT_T be a feature set of template fingerprint.

$$FT_T = \{D_{ij}', D_{jk}', D_{ik}', \Psi_i', \Psi_j', \Psi_k', OZ_i', OZ_j', OZ_k', \alpha_i', \alpha_j', \alpha_k', T'_i, T'_j, T'_k\} \quad (5)$$

These two attribute set of local triangles of query and registered fingerprints are used to compute the similarity between fingerprints. Following fuzzy rules are applied to measure the similarity between fingerprints as follows:

$$\overrightarrow{D_{diff}} = \{|D_{ij} - D_{ij}'|, |D_{jk} - D_{jk}'|, |D_{ik} - D_{ik}'|\} \quad (6)$$

$$\overrightarrow{\Psi_{diff}} = \{|\Psi_i - \Psi_i'|, |\Psi_j - \Psi_j'|, |\Psi_k - \Psi_k'|\} \quad (7)$$

$$\overrightarrow{OZ_{diff}} = \{|OZ_i - OZ_i'|, |OZ_j - OZ_j'|, |OZ_k - OZ_k'|\} \quad (8)$$

$$\overrightarrow{\alpha_{diff}} = \{|\alpha_i - \alpha_i'|, |\alpha_j - \alpha_j'|, |\alpha_k - \alpha_k'|\} \quad (9)$$

Also, we compare a minutiae type of three coordinates of triangular pairs. These are legitimate distorted pattern parameters.Steps involved in the enhanced fuzzy feature match*(EFFM)* are as follows:

Step 1: Legitimate features of each minutia such as x-y coordinates, orientation angle and minutiae type are extracted.

Step 2: Construct feature vectors of each triangle of query and templatefingerprint.

Step 3: Clusters are designed using Cauchy membership function. All elements in the genuine distorted pattern parameter space construct the fuzzy feature set F_i. The centre $\overline{f_j}$of a clusteris defined as:

$$\overline{(f_j)} = \frac{\sum_{\bar{f} \in F_j} \bar{f}}{V(F_j)} \quad (10)$$

which is essentially the mean of all elements of (F_j). Accordingly, the region is represented by fuzzy feature F_j whose membership function,

$$\mu_{F_j}(\vec{f}) = \frac{1}{1 + \left(\frac{|\vec{f} - \vec{f_j}|}{d_f}\right)^{\alpha}} \quad (11)$$

where $d_f$is the average distance between the cluster centers.The similarity vectors are constructed by using fuzzy similarity. The similarity vector$\vec{l}^A$for every $\overrightarrow{FT_k} \in T$ is constructed by combining all the similarity vectors.

$$\vec{l}^A = [l_1^A, l_2^A, \ldots \ldots, l_{C_a}^A] \quad (12)$$

For every$\overrightarrow{FT_t} \in T$, construct a similarity vector$\vec{l}^B$

$$\vec{l}^B = [l_1^B, l_2^B, \dots \dots, l_{C_a}^B] \quad (13)$$

Thus, we define a combined similarity vector for query and template images as

$$\vec{L}^{(A,B)} = \begin{bmatrix} \vec{l}^B \\ \vec{l}^A \end{bmatrix} \quad (14)$$

A measure of similarity between template and input fingerprints is defined as

$$Sim = [(1-p)\underset{w_A}{\rightarrow} + p\underset{w_B}{\rightarrow}]\underset{L^{(A,B)}}{\longrightarrow} \quad (15)$$

Where $p \in [0,1]$gives the significance of $\underset{w_A}{\rightarrow}and\underset{w_B}{\longrightarrow}$.

Step 4: Find a matched pair of feature vector between query and template fingerprint by using fuzzy rules expressed in eq. 6,7,8,9.

Step 5: Search matched triangles which are attached to the previouslymatched triangle.

Step 6: If no two triangles are matched, consider newfeature vector and repeat step 4) and 5).

Step 7: If the number of matched triangles is maximum, features of corresponding exemplar are considered for the reconstruction of input fingerprint.

Step 8: Similarity Score is again computed. Now,feedback is required or not. If feedback is needed, then repeat from steps 4) to 7).

To compute a similarity score, we use eq. 19. In a firstpass, we compute a similarity score of input and query fingerprints, which is considered as an initial similarity score*Sim_I*. Let I^Ibe an input fingerprint and I^Tbe an exemplar fingerprint image from registered or existing database. Let $FT_I$and FT_T be feature sets of input and exemplar fingerprints, respectively. These feature sets are used to computeinitial similarity score Sim_I.

$$Sim_I = S_I(FT_I, FT_T) \quad (16)$$

Then, we find out top *K*candidates having high matching score, which are considered as exemplar candidates.Now, use the features of these exemplar candidates to reconstruct or refine the features of input fingerprint. LetFT_I' be a refined feature set computed using following formula.

$$FT'_I = f(FT_I, F) \quad (17)$$

Aftera refining the features, Again, compute an updated similarity score Sim_U which is considered as feedbackmodel.

Updated similarity score is evaluated as follows:

$$Sim_U = Sim_I \otimes Sim_F \quad (18)$$

After each pass, we check whether feedback is essential ornot. If input fingerprint is of good quality, feedback is no required. To decide whether feedback is required or not, we use a global criterion based on the match score distribution analysis observed by computing the similarity between input fingerprint and top *K* exemplars. The ridge continuity is checked. For reconstruction of orientation of distorted input fingerprint, whether the region within exemplars of good quality is required or not, is determined using local criterion.

3.4 Feedback Paradigm Computation

As we mentioned in the introduction, to renovate the desired features of the query fingerprint image, we use the feedback paradigm.But, first we need to check whether feedback is required or not. If the quality of the query fingerprint image is good, feedback is not needed. Otherwise, we need the feedback for the renovation of the desired features, which in turn, improve the matching performance.The decision to apply apply feedback is global as well as local. Because feedback is applied on each block of the query image. Global criterion is used to check the quality of the query fingerprint image. Image is blocked into 16X16 blocks. Then sub-image $I_C(x,y)$ of size 32X32 is acquired..By padding zeros to $I_C(x,y)$, a sub-image $I^*_C(x,y)$ is obtained.

3.4.1 Global Criterion

To deicide the feedback is to be computed for the current query fingerprint image, the principle of the probability match score distribution of top *K*images is used. The match score distribution is based on the enhanced fuzzy feature match. Theexponential probability distribution function of the match score is to check the global criterion. Here, if true fingerprint is matched in the first pass, then there will be noticeable variation between the match score of true mated fingerprint and other.The match score of this true mated fingerprint is considered as an upper outlier. In global criterion, to check whether feedback is needed, we check the presence of the upper outlier(Sunpreet S. Et al, 2015).Eq. 19 is the probability distribution function of exponential distribution:

$$f(x) = \frac{1}{\lambda} e^{-\frac{x}{\lambda}}; x > 0; \lambda > 0. \quad (19)$$

Here, X is the set of top *K*match scores. $X_1<X_2<X_3<......<X_n$. To check the upper outlier, null hypothesis and alternative hypothesis are considered. In null hypothesis H_0, the match score of all the top *K* exemplars is considered. On the otherside, the maximum match score of an upper outlier is considered. The test statistic *Z* to test the hypothesis is expressed in Eq. 20.

$$Z = \frac{X_n - X_{n-1}}{S_n}; S_n = \sum_{i=1}^{n} X_i \quad (20)$$

Find out the difference between two variables Z_1 and Z_2. $Z_1=X_n/S_n$ and $Z_2=X_{n-1}/S_n$.Now, the critical value $z(\alpha)$ is given in Eq. 21:

$$z(\alpha) = 1 - \alpha^{\frac{1}{n-1}} \quad (21)$$

Here, in global criterion, to decide whether feedback is required or not, we use a variable R_f. The value of $R_f$is 0, if the upper outlier is presentand the value of test statistic *Z* of the upper outlier is larger than $z(\alpha)$.If the value of R_f is 1, it means feedback is needed, otherwise it is 0, if feedback is not needed.

$$R_f = \begin{cases} 0, & z > z(\alpha) \\ 1, & otherwise \end{cases} \quad (22)$$

3.4.2 Local Criterion

We have seen that we use global and local criterion to decide feedback is needed or not.As seen in section 3.4.1, global criterion is applied to check the overall quality of query image. But it may happen that few regions of query image are good in quality, and does not require a feedback. To check whether feedback is required locally, we apply local criterion on each block of query fingerprint image. Now, the exemplar region from which feedback is taken, it should of good quality. If this region is of poor quality, then the feedback taken from it is not trustworthy.The principle of the ridge clarity is used to check the need of feedback locally. We compute the ridge clarity map and the ridge continuity map(Sunpreet S. Et al, 2015).

a) ***Ridge continuity map computation:*** Two adjacent blocks B_1 and B_2 are said to continuous if following conditions are true for their sine waves Bw_1 and Bw_2.

$$\min\{|B\theta_1, B\theta_2|, \pi - |B\theta_1, B\theta_2|\} \le T_{B\theta},$$

$$\left|\frac{1}{Bf_1} - \frac{1}{Bf_2}\right| \le T_{Bf},$$

$$\frac{1}{16}\sum_{(p,q\in\psi)}\left|\frac{Bw_1(p,q)}{Ba_1} - \frac{Bw_2(p,q)}{Ba_2}\right| \le T_{Bp} \quad (23)$$

Where $T_{B\theta}$, = π/10, T_{Bf}, =3 and T_{Bp} =0.6. ψ is used to consider the set of 16 pixels located on the border of two adjacent blocks. The indicator variable I_{rcr} is used to define the ridge clarity as mentioned in Eq. 24.

$$I_{rcr} = \begin{cases} 1, & Bw_1 \text{ and } Bw_2 \text{ continuous} \\ 0, & \text{otherwise} \end{cases} \quad (24)$$

The ridge continuity map $R_{conuntinuity}$ is computed as follows:

$$R_{continuity}[p,q] = \sum_{[p^*,q^*\in N]} \max\begin{Bmatrix} I_{rcr}(w_1(p,q), w_1(p^*,q^*)), \\ I_{rcr}(w_2(p,q), w_2(p^*,q^*)) \end{Bmatrix} \quad (25)$$

b) ***Ridge clarity map computation:*** Ridge clarity map is computed by using Eq. 26.

$$R_{clarity}[p,q] = a_1(p,q) \times R_{continuity}[p,q] \quad (26)$$

Where $a_1(p,q)$ is the amplitude of pixel *(p,q)*.To define whether a particularregion of the query image need feedback or not, we an indicatorvariable I_{lf}in eq. 27. If $R_{clarity}[p,q]$ is greater than Th_1, $I_{lf}$is 1, else 0.

$$I_{lf} = \begin{cases} 1 & I^Q(R_{clarity}[p,q]) > Th_1 \\ 0 & \text{otherwise} \end{cases} \quad (27)$$

In the same way, the region of the exemplar image from which we can take a reliable feedback, we use an indicator variable I_{ef}.

$$I_{ef} = \begin{cases} 1 & I^E(R_{clarity}[p,q]) > Th_2 \\ 0 & \text{otherwise} \end{cases} \quad (28)$$

IV. RESULT ANALYSIS

In our system, to analyze the performance f the proposed system, we used various databases like FVC2004, fingerprint images taken from the users by using SecGen fingerprint scanner.False acceptance rate(FAR) is the probability that two false fingerprint images are recognized as matched fingerprints. False Rejection Rate (FRR) is the probability that two true fingerprint images are recognized as matched fingerprints. Genuine Acceptance Rate(GAR) is a score which indicates genuineusers accepted by system. To analyze the performance of the proposed *EFFM*, we used FAR, FRR and GAR and also the similarity distribution graph. FAR, FRR and GAR are calculated using following formulae eq. 29, 30 and 31.

a) False Acceptance Rate (FAR)

$$FAR = \frac{Number\ \ of\ accepted\ \ Legitimate\ \ imposter}{Total\ imposter} \quad (29)$$

b) False Rejection Rate (FRR)

$$FAR = \frac{Number\ \ of\ accepted\ \ Legitimate\ \ imposter}{Number\ \ of\ rejected\ \ Legitimate\ \ imposter} \quad (30)$$

c) Genuine Acceptance Rate (FAR)

$$FAR = \frac{Number\ \ of\ accepted\ \ Genuine\ \ imposter}{Total\ imposter} \quad (31)$$

4.1 Database

4.1.1 FVC2004

The Biometric System Lab(University of Bologna), thePattern Recognition and Image Processing Laboratory ofMichigan State University and San Jose State Universitycollected FVC2004 (the Third International Fingerprint Verification Competition). FVC2004 database contains more challenging images than FVC2002 database and are superior to scrutinizethe performance of proposed algorithm.. It consists 4sets of databases DB1fiB, DB2fiB, DB3fiB and DB4fiB. Each database contains 110 fingers wide and 8 samples per finger in depthof the size of 640X480 pixels withthe resolution 500ppi(Shubhangi et al, 2016).

Sr. No.	Database	Image	Resolution
1	DB1	640X480	500dpi
2	DB2	328X364	500dpi
3	DB3	300X480	512dpi
4	DB4	288X384	500dpi

Table 1. FVC2004 Database Details

4.1.2 Input from SecuGen Scanner

In this paper, we focused on distortion caused due to a dark colored *Mehndi*on fingers. For distorted fingerprints acquisition, we used SecuGen Hamster IV USB fingerprint scanner, which can capture fingerprints with *Mehndi*. We acquired a real database. So, we took 300 different fingerprint images from 300 users to analyze the performance of the system. These images are of 500ppi and of size 258X236. From Fig. 1, we can analyze that fingerprints with *Mehndi*are of very poor quality and contain less amount of the desired features.

4.2 Performance of Matcher over FVC2004 Database

In general, ideal biometric system should have less FRR and FAR and more GAR also. It's performance is tested over four datasets of FVC2004, shown in fig. 5. In all the graphs, FAR and FRR are declining. GAR curve is rising. Our system performance is better over FVC2004 database. FAR, FRR and GAR are computed(Shubhangi et al, 2016).

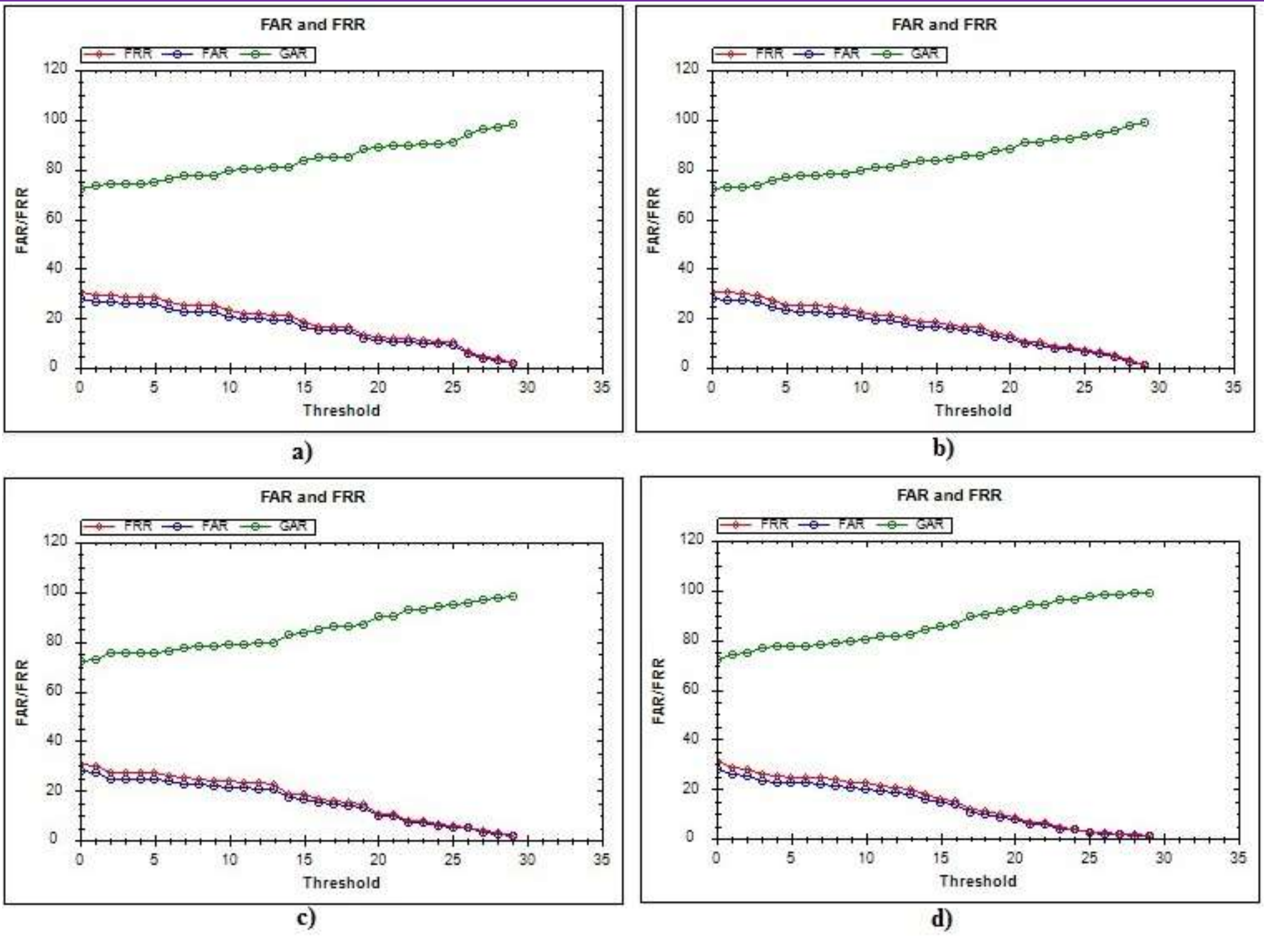

Fig. 5. Performance of matcher over a) DB1_B b) DB2_B c) DB3_B d) DB4_B

4.3 Performance of Matching Algorithm

4.3.1 Computational Complexity

Features of only top K exemplars are usedfor reconstruction instead of all database images,time complexity is O(K). The proposedalgorithm is implemented in C# on a desktop system with Intel 2 Duo CPU of 2.92 GHz and 2.00 GB of RAM withWindows 8 64bit Operating system.

4.3.2Performance on SecGen Database

We collected 300 *Mehndi*fingerprint images from 300 different users to test and analyze the accuracy and performance of the proposed algorithm. Fig. 6. shows the similarity score distribution of aim6.bmp *Mehndi*fingerprint image over exemplar images. Fig. 7.shows FAR, FRR and GAR for SecuGen database images which are of size 258X236 with 500ppi resolution. Ideally, FRR and FAR should be reduced and GAR should be increased. A graph shows that, for SecuGen database FRR and FAR curves are declining and GAR curve is rising.

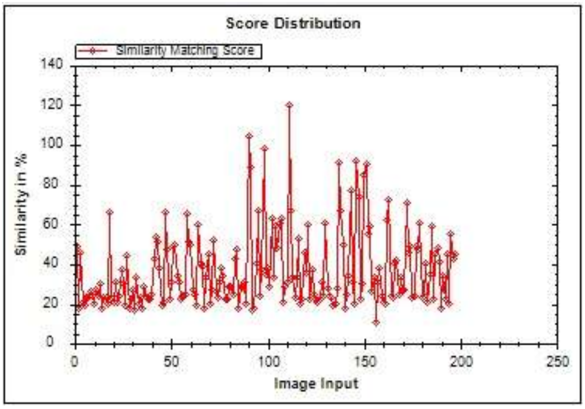

Fig. 6. Similarity Score Distribution for aim1.bmp image

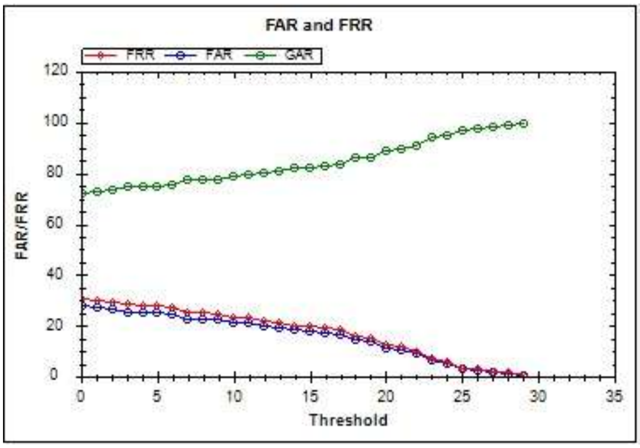

Fig. 7. Performance of EFFM over SecuGen database

ISSN: 2454-4248
188 – 197

In Table 2, FAR, FRR and GAR are mentioned in percentage. As mentioned in section 4, ideally FAR and FRR should be reduced and GAR should be increased. The proposed system shows better performance over FVC2004 database images. For Secugen database, GAR is 94.1686, which can be improved further.

Sr. No.	Database	FAR(%)	FRR(%)	GAR(%)
1	FVC2004 DB1 B	1.9294	1.7428	98.2572
2	FVC2004 DB1 B	0.9646	0.8714	99.1286
3	FVC2004 DB1 B	2.2772	2.0569	97.9430
4	FVC2004 DB1 B	1.1300	1.0207	98.9793
5	SecuGen Database	2.03755	5.8314	94.1686

Table 2. Result Analysis

V. CONCLUSION AND FUTURE WORK

To handle geometric distortion has becomea prominent research dilemma. In this paper, wetried to concentrate on geometric distortions which mainlyoccur due to dark colored *Mehndi*on fingers. To remove spuriousminutiae, fuzzy logic is applied as fuzzylogic handles uncertainties and more efficient.Orientation field is reconstructed using enhancedfeedback which uses prior knowledgewhich leads to the improvement in the accuracyof fingerprint matching. Enhanced fuzzy feature match*(EFFM)* is usedfor fingerprint matching which increases GAR, FRRand minimizes FAR.

Further, to enhance an algorithm, the ridgefeatures can also be integrated with minutiaefeatures to measure the correspondence betweenfingerprints. In future, we will focus to detectthe distortion field in fingerprint images.

References

[1] D. Maltoni, D. Maio, A. Jain, S. Prabhakar. *Handbook of Fingerprint Recognition (Second Edition)*. Springer, 2009.

[2] Xuanbin Si, Jianjiang Feng, Jie Zhou, Yuxuan Luo, “Detection and Rectification of Distorted Fingerprints,” *IEEE Transactions On Pattern Analysis And Machine Intelligence*, vol. 37, no. 3, 2015.

[3] S. Ingale, A. Butalia, “Distorted Fingerprint Matching Performance Improvement Based on Fuzzy Logic,” *International Journal of Computer Science and Information Technology Research*, ISSN 2348-120X (online), vol. 3, no. 4, pp. 243-249, ISSN 2348-1196 (print), October - December 2015.

[4] Xiaoguang He, Jie Tian, Liang Li, Yuliang He, Xin Yang, “Modeling and Analysis of Local Comprehensive Minutia Relation for Fingerprint Matching,” *IEEE Transactions On Systems, Man, And Cybernetics*, vol. 37, no. pp. 1204 – 1211, Oct. 2007.

[5] Zadeh L A, *Fuzzy sets. Inform. Contr*. 8:338-53, 1965. [Dept. Electrical Engineering and Electronics Res. Lab., Univ. California, Berkeley, CA]

[6] G.J. Klir, B.Yuan, *Fuzzy Sets and Fuzzy Logic: Theory and Applications*, Prentice-Hall, India, 1997.

[7] N. K. Ratha, R. M. Bolle,“Effect of controlled image acquisition on fingerprint matching,”*ICPR 98, Brisbane*, vol.2, pp. 1659-1661, Aug. 1998.

[8] Chitra Dorai, Nalini Ratha, Ruud Bolle, “Detecting dynamic behavior in compressed fingerprint videos: Distortion,” in *Proceedings of Computer Vision and Pattern Recognition*, pp. 320–326, June 2000.

[9] Xinjian Chen, Jie Tian, Xin Yang, “A New Algorithm for Distorted ... Fuzzy Similarity Measure,,” *IEEE Transactions On Image Processing*, vol. 15, no. 3, pp. 767 – 68, March 2006.

[10] Jaba Malar, R. Kavitha; Raj, V. Joseph, “Controlled Triangularization Fingerprint Verification Inscribed in a Rhombus Using Fuzzy Feature Matching,” International Journal of Computer & Electrical Engineering,” vol. 6, no. 2, pp. 123 - 126, April 2014.

[11] Nguyen Thi Huong Thuy, Hoang Xuan Huan, Nguyen Ngoc Ky., “An Efficient Method for Fingerprint Matching Based on Local Point Model,” *IEEE International Conference on Computing, Management and Telecommunications*, January 2013.

[12] Soweon Yoon, Jianjiang Feng, Anil K. Jain. “Altered Fingerprints: Analysis and Detection,” *IEEE Transactions On Pattern Analysis And Machine Intelligence*, vol. 34, pp. 451–464, 2012.

[13] Xuanbin Si, Jianjiang Feng, Jie Zhou, Yuxuan Luo, “Detection and Rectification of Distorted Fingerprints,” *IEEE Transactions On Pattern Analysis And Machine Intelligence*, vol. 37, 2015.

[14] Kai Cao, XinYang, Xinjian Chen, YaliZang, JiminLiang, JieTian, “A novel ant colony optimization algorithm for large-distorted fingerprint matching,” *Elsevier Journal ofPattern Recognition*, vol. 45, pp. 151-161, 2012.

[15] Heeseung Choi, Kyoungtaek Choi, Jaihie Kim, “Fingerprint Matching Incorporating Ridge Features With Minutiae,” *IEEE Transactions On Information Forensics And Security*, vol.6, 2011.

[16] Alessandra A. Paulino, Jianjiang Feng, Anil K. Jain, “Latent Fingerprint Matching Using Descriptor-Based Hough Transform,” *IEEE Transactions On Information Forensics And Security*, vol. 8, 2013.

[17] Jianjiang Feng, Jie Zhou, and Anil K. Jain, “Orientation Field Estimation for Latent Fingerprint Enhancement,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 4, pp. 925-939, 2013.

[18] Xiao Yang, Jianjiang Feng, Jie Zhou, “Localized Dictionaries Based Orientation Field Estimation for Latent Fingerprints,” *IEEE Transactions On Pattern Analysis And Machine Intelligence*, vol. 36, no. 5, pp. 955-968, 2014.

[19] Alessandra A. Paulino, Jianjiang Feng, Anil K. Jain, “Latent Fingerprint Matching Using Descriptor-Based Hough Transform,” IEEE Transactions On Information Forensics And Security.

[20] Kai Cao, Anil K. Jain, “Learning Fingerprint Reconstruction: From Minutiae to Image. *TIFS*,” 2014.

[21] Kai Cao, Anil K. Jain, “Latent Orientation Field Estimation via Convolutional Neural Network,” *IEEE ICB Conference*, 2015.

[22] M. Sadhana, K. Thangavel, K. Sasirekha, “Fingerprint Recognition using Fuzzy Back Propagation Neural Network,” *Indian Journal of Engineering*, vol. 12, pp. 308 – 312, September 2015.

[23] Pooja Naval, Dr. Girish Kumar Patnaik, Sandeep S. Patil, "Wrinkled Fingerprint Veri_cation using BPNN and Minimum Distance Features between Singularities,"

ISSN: 2454-4248
188 – 197

International Journal of Advanced Engineering and Global Technology, vol. 2, no. 4, April 2014.

[24] Sunpreet S. Arora, Eryun Liu, Kai Cao, "Latent Fingerprint Matching: Performance Gain via Feedback from Exemplar Prints," *IEEE Transactions On Pattern Analysis And Machine Intelligence*, vol. 36, 2014.

[25] H. D. Cheng, X.J. Shi, "A simple and effective histogram equalization- approach to image enhancement," *Journal of Digital Signal Processing*, vol. 1, pp. 158-170, 2004.

[26] Muna F. Hanoon, "Contrast Fingerprint Enhancement Based on Histogram Equalization Followed By Bit Reduction of Vector Quantization," *IJCSNS International Journal of Computer Science and Network Security*, vol. 11, 2011.

[27] T. Romen Singh, Sudipta Roy, O. Imocha Singh, TejmaniSinam, Kh. Manglem Singh, "A New Local Adaptive Thresholding Technique in Binarization," *International Journal ofComputer Science Issues*(*IJCSI*), vol. 8, 2011.

[28] Roli Bansal, Priti Sehgal, Punam Bedi, "Minutiae Extraction from Fingerprint Images - a Review," *International Journal of Computer Science Issues*, vol 8, 2011.

[29] M. James Stephen, Prof. Prasad Reddy P.V.G.D, Prof.K.R.Sudha, "Removal of False Minutiae with Modified FuzzyRules," *IFRSAs International journal of Computing*, vol. 3, no. 3, 2013.

[30] Xinjian Chen, Jie Tian, Xin Yang, Yangyang Zhang, "An Algorithm for Distorted Fingerprint Matching Based on Local Triangle Feature Set," *IEEE Transactions On Information Forensics And Security*, vol. 1, 2006.