ORIGINAL RESEARCH

Singular-minutiae points relationship-based approach to fingerprint matching

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Received: June 8, 2015 **Accepted:** August 18, 2015 **Online Published:** November 3, 2015
DOI: 10.5430/air.v5n1p78 **URL:** http://dx.doi.org/10.5430/air.v5n1p78

ABSTRACT

Key issues with several of the existing fingerprint matching algorithms include problem of alignment of two minutiae feature vectors, failure with noisy image and nonlinear distortions. In this study, singular-minutiae points relationship-based algorithm is proposed for addressing the problem of alignment of two minutiae feature vectors in fingerprint matching. The algorithm uses the minutiae in the neighborhood of the core or delta point for promoting accuracy and reduction in computation by taking advantage of the fact that same source images of equal dimensions maintain same distance for every minutia point and the core/delta point irrespective of orientation. Results of experiments on local fingerprints and FVC2006 standard fingerprint databases were classified into correct, false positive and false negative. With correct results, the reference fingerprint is correctly matched to one or more fingerprints from the same person while in the case of false positive; the reference fingerprint is matched to one or more fingerprints of another person. False negative results were recorded for cases where the reference image refused to match with any of the fingerprints in the database. Based on FVC2006 fingerprints database, the Receiver Operating Characteristics (ROC) curves were also generated for the proposed algorithm and some recently formulated ones. Analysis of obtained results in all cases shows very good performance of the new algorithm.

Key Words: Fingerprint matching, Fingerprint verification, Minutiae and singular points, Feature vector, Standard fingerprint database

1. INTRODUCTION

Fingerprint matching has featured prominently as a reliable biometric technique in several human automatic identification and verification systems. During fingerprint verification, the identity of an individual is investigated based on his or her fingerprint properties. Fingerprint identification is used to establish the identity of an individual and it involves matching a query fingerprint against fingerprints in a database.[1] In most cases, matching is based on pre-determined fingerprint features known as *minutiae*. The commonly used minutiae are the ridge end and bifurcation points[2,3] whose forms are shown in the raw and skeleton images of Figure 1.

The minutiae set for a fingerprint is formed from its existing minutiae points with each point described by location, orientation, type and other local information such as ridge count and the quality of the region around it. Based on a minutiae description, fingerprint matching is simply taken as a point matching problem which implies determining a subset of minutiae in the reference fingerprint that optimally matches to a subset of minutiae in the template fingerprint based on a geometric transformation in the most reasonable sense.[4] Challenges confronting fingerprint matching include large

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intra-class and the small inter-class variations. Intra-class variations are the variations among different impressions of the same finger while inter-class variations are variations among images of different fingers. The fundamental reasons for the large intra-class variations include partial overlap, non-linear distortion and sensor noise. Due to rotation and displacement of the finger placed on the sensor, there is often only a partial overlap between the template and query fingerprint images.[5,6]

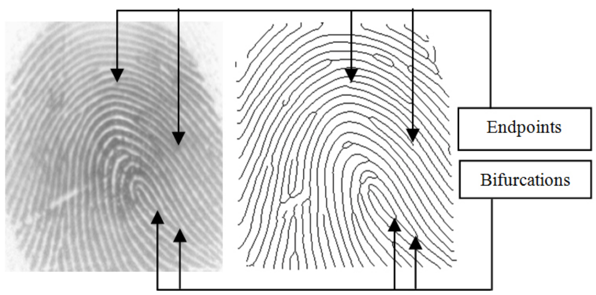

Figure 1. Ridge end and bifurcation points in raw and skeleton images

Several studies on these problems have culminated into the development of a number of algorithms for the elimination or reduction of their effects on matching. Some of these algorithms are correlation based, minutiae-based and ridge feature-based.[1,7–14] The matching of two minutiae sets is usually posed as a point pattern matching problem and the similarity between them is proportional to the number of matching minutiae pairs.

Although the minutiae pattern of each finger is quite unique, contaminants and distortion during the acquisition and errors in the minutia extraction process result in a number of missing and spurious minutiae. Due to difficulty in obtaining minutiae points from poor quality fingerprint images, other ridge features like the orientation and the frequency of ridges, ridge shape and texture information have formed the bedrock for several fingerprint matching algorithms. However, several of these methods suffer from low identification capability. In correlation-based fingerprint matching, the template and query fingerprint images are spatially correlated to estimate the degree of similarity between them. If the rotation and displacement of the query with respect to the template are not known, then the correlation must be computed over all possible rotations and displacements, which is computationally very expensive. Furthermore, the presence of non-linear distortion and noise significantly reduce the global correlation value between two impressions of the same finger. To overcome these problems, correlation is locally done around the high curvature, minutia information and other interesting regions of the fingerprint image.

On the basis of Delaunay Triangulation (DT) in computational geometry, fingerprint matching algorithms were proposed in Refs.[4,15,16] DT is often used to find Reference Minutiae Pairs (RMPs) and its network is formed with minutiae as vertexes. From the networks of the input and template minutiae sets, certain pairs of minutiae which have similar structures as RMPs are selected for aligning and matching based on point pattern. From several RMPs, the accuracy of results on rotation and translation of fingerprint has been greatly improved with corresponding effort of matching. In addition, DT network is not influenced by the change of resolution ratio of fingerprint image. The key issue with most DT-based algorithms include problem of alignment of two minutiae feature vectors, failure with noisy image and nonlinear distortions. In this study, singular-minutiae points relationship-based algorithm is proposed for addressing the problem of alignment of two minutiae feature vectors in fingerprint matching.

2. Singular-minutiae point relationship-based fingerprint matching (SMP)

The minutiae extracted from a fingerprint are often regarded as a set of scattered points around the singular point on the plane. The singular point is defined as the point where the ridge curvature is higher than normal with the direction of the ridge changes rapidly. It is also considered as the point where the orientation field is discontinuous. Singular points can be classified into two types; namely core and delta which are shown in Figure 2.[17]

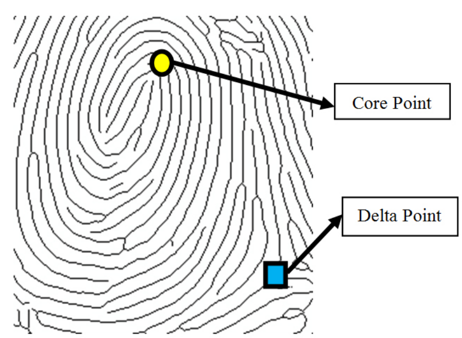

Figure 2. Fingerprint showing the core and delta points

At the core point, the pattern exhibits the semi-circular tendency whereas the patterns split into three different sectors at the delta point, and each sector exhibits the hyperbolic tendency.[18,19] The network of connection between each minutia point and the singular point produced a suitable pattern and rule for good performance in the determination of uniqueness and local stability. The SMP-based fingerprint matching uses the fixed distances between minutiae and the core point or delta point as illustrated in Figure 3.

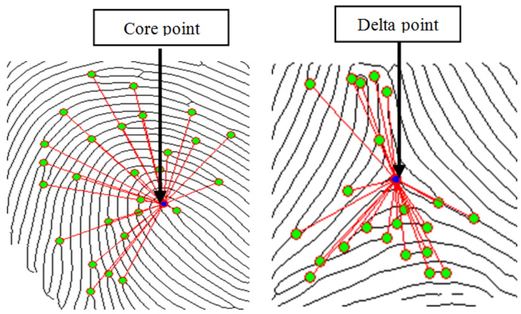

Figure 3. Singular and minutiae point interconnections

Any reasonable fingerprint enrolment must capture the core/delta point with significant number of minutiae around it.[20] This formed the basis for the use of minutiae points within radius R of the core or delta point for promoting accuracy and reduction in computation. In addition, consideration is also given to the fact that same source images of equal dimensions maintain same distance for every minutia point and the core/delta point irrespective of orientation. The procedure for the extraction of the minutiae and core/delta points is conceptualized in Figure 4. The fingerprint image enhancement phase performs image segmentation, normalization, ridge orientation estimation, ridge frequency estimation, ridge filtering, binarization and thinning in succession based on the algorithms presented in Refs.[3,21–23] for the elimination of noise and contaminants.

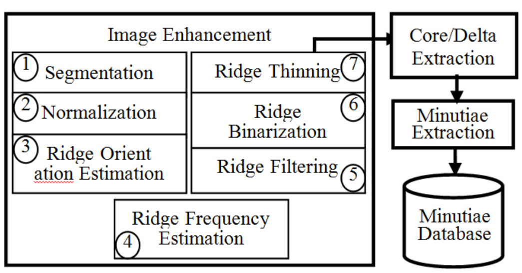

Figure 4. Conceptualization of the algorithm

Image segmentation is concerned with the extraction of regions with noise-free ridges and valleys and helps in the exclusion of the noisy regions[2] from the subsequent stages. The segmented ridges and valleys are normalized to produce an image with uniform and standardized contrast during normalization. The orientation of the ridges in the normalized image is obtained as a prelude to the ridge directional flow which is a basic parameter for ridge frequency estimation. Ridge frequency is the reciprocal of ridge distance indicating the number of ridges within a unit length of an image and its estimation is concerned with the local frequency of the ridges that collectively formed the ridge frequency image. During fingerprint ridge filtering, high-pass filter in which the pre-obtained ridge orientation and frequency estimates are used as parameters, is used to remove all forms of noise from the images. Binarization and thinning are performed to obtained binarized and skeleton versions respectively for the filtered image. The core/delta points were extracted based on Poincare index algorithm.[17,24] The core point was given preference but in cases where it does not exist, the delta point is extracted. The minutiae extraction phase extracts the (x, y) coordinate of both the true and false ridge end and bifurcation points from the image. The isolated, continuous and crossing points in a fingerprint image produced spur, hole, triangle and spike structures that are regarded as false minutiae points. The spur structure generates false ridge endings while the hole and triangle structures produce false bifurcations (see Figure 5). The spike structure also creates a false bifurcation and a false ridge ending point.[25,26]

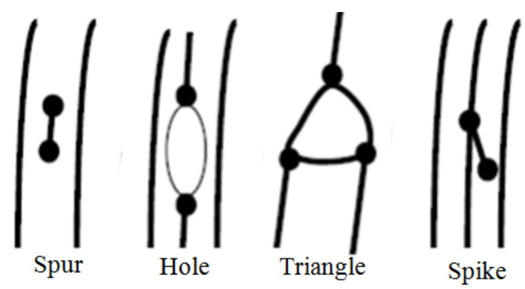

Figure 5. False Minutiae Structures

The extraction is based on the gray-level values of the pixels in the 3×3 neighbourhood and a minutia point is extracted based on a value, P obtained from:[3,26]

$$P = \sum_{i=0}^{7} |N_{i+2} - N_{i+1}|, N_9 = N_1 \quad (1)$$

$N_1, N_2, \cdots, N_8$ represent the 8 neighbours of the candidate pixel S, in its 3×3 neighborhood which are scanned in the direction shown in Figure 6.

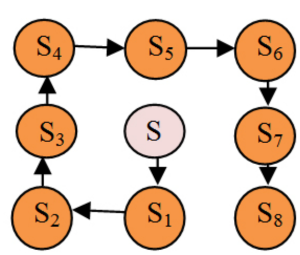

Figure 6. Eight neighbors of a candidate minutiae point

$P = 2$ denotes a ridge end while P value of 6 represents a ridge bifurcation point. The isolated ($P = 0$), continuous ($P = 4$) and crossing points ($P = 8$) produced spur, hole, triangle and spike structures[22,26] which are regarded as false minutiae points. For a very reliable fingerprint matching, a minutia validation algorithm is applied for excluding every false minutia point.[26]

The validation algorithm creates an image M of size $W \times W$ and centred on the candidate minutia point. The validity of the candidate point is then tested by examining the properties of its 3×3 neighbourhood. This involves labelling the centre pixel with -1 while the connected pixels are initialized to zero, as shown in Figure 7(a) and Figure 7(c) for candidate ridge ending and bifurcation points respectively. Next, for every ridge end candidate point, all the connecting pixels are initialized to 1 (see Figure 7(b)) and the number of 0 to 1 transitions in clockwise direction (T01) along the border of M is determined.

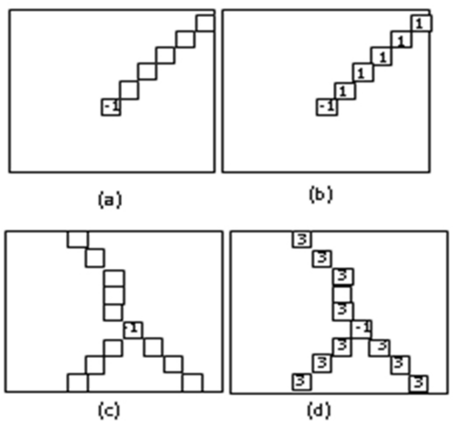

Figure 7. Labeling and initialization of Candidate minutiae points and its connected pixels

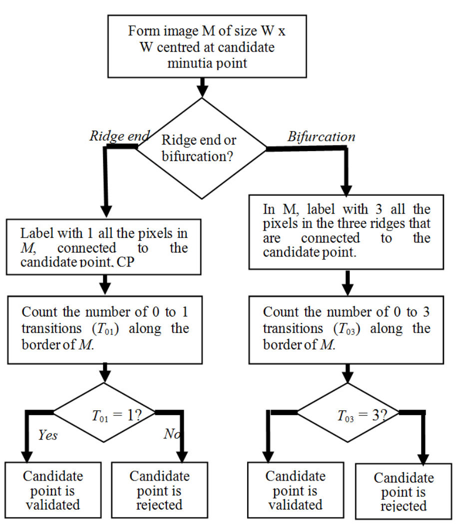

Figure 8. Flowchart for minutiae validity test

If T01 = 1 (see Figure 7(b)), then the candidate minutia point is a true ridge ending. Similarly, for each bifurcation point, all the three ridge pixels in M that are connected to it are initialized to 3 and the number of transitions from 0 to 3 (T03) (see Figure 7(d)) are counted along the border of image M in clockwise direction. If T03 = 3, then the candidate point is validated as a true bifurcation point. The extracted true minutiae points formed the reference minutiae set and the flowchart of the algorithm is presented in Figure 8.

3. SMP-BASED FINGERPRINT MATCHING

The SMP-based matching of reference (R) and template (T) fingerprint images is in the following phases:

(1) From the reference thinned image R, extract the core/delta point $X(a_c, b_c)$.

(2) For each of M minutiae points $X(a_i, b_i)$ within radius R of the core/delta point, compute the Euclidian distance $\overline{XY_i}$ to the core/delta point $X(a_c, b_c)$ as follows:

$$\overline{XY_i} = \sqrt{(a_c - a_i)^2 + (b_c - b_i)^2} \tag{2}$$

$$S_R = \downarrow \overline{XY_i} \tag{3}$$

$i = 1, 2, \cdots, M$ and $\downarrow$ represents the "Sort from smallest to highest" operation. $S_R(1), S_R(2), S_R(3), \cdots, S_R(M)$ gives the order of closeness of the M minutiae points to $X(a_c, b_c)$. The chains of connection between the extracted core/delta point and the minutiae points within its circular region of radius R are shown for the images presented in Figure 9.

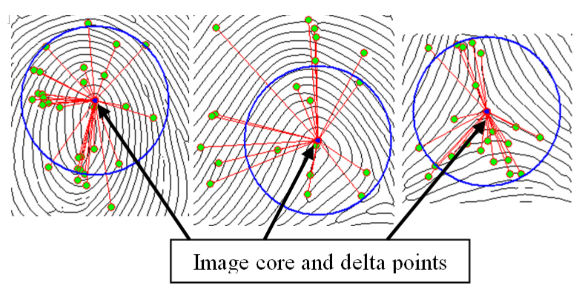

Figure 9. A minutia points and its interconnecting lines to other points

(3) Based on pre-extracted core/delta and minutiae sets of the template (T) image in the minutiae database, operation (b) is repeated to obtain $S_T(1), S_T(2), S_T(3), \cdots, S_T(M)$.

(4) The matching weight, W for ith nearest minutiae points in R, of type N_R^i and in T, of type N_T^i is obtained from (given that $N_R^i = N_T^i$):

$$W_i = \begin{cases} 1 & |S_R(i) - S_T(i)| < H \, and \, N_R^i = N_T^i \\ 0 & otherwise \end{cases} \tag{4}$$

H is a scalar representing the difference threshold and $i = 1, 2, \cdots, M$. If $N_R^i \neq N_t^i$, then

$$W_i = 0 \tag{5}$$

(5) The cumulative weight, W_{RT} for R and T is obtained from:

$$W_{RT} = \sum_{s=1}^{M} W_s \tag{6}$$

(6) The matching score γ for R and T is derived from:

$$\gamma = \frac{W_{RT}}{M} \tag{7}$$

If γ equals or exceeds the matching threshold MT, then the two images are said to match.

4. Experimental study

The implementation of the proposed fingerprint matching algorithm was carried out using Matlab version 7.6 on Microsoft Window Vista Home Basic Operating System which ran on a Pentium 4 – 2.10 GHz processor with 4.00 GB of RAM. The implementation provided the basis for the evaluation of the performance of the proposed algorithm under different condition of images. It also allowed the generation of metric values that could be used to compare the performance of the algorithm with that of some recently formulated ones.

4.1 Fingerprint datasets

Case studies of local and benchmark fingerprints were carried out. The summary of the local fingerprints is presented in Table 1. Ten fingerprints were enrolled in two sessions from the same finger of each of 500 randomly selected subjects. In the first session, UareU fingerprint scanners were used at image resolution 500 dpi and size 400×300. In the second session, SecuGen fingerprint scanners were used at the same specifications and subjects. The benchmark FVC2006 fingerprints were obtained from Fingerprint Verification Competition[27] and its summary is presented in Table 2.

Table 1. Details of local fingerprint databases

Dataset	Sensor type	Image size	Set A(w × d)	Resolution
DB1	UareU	400 × 300 pixels	500 × 10	500 dpi
DB2	SecuGen	400 × 300 pixels	500 × 10	500 dpi

Table 2. Details of FVC2006 fingerprint database

Data set	Sensor Type	Image size	Set A(w×d)	Set B(w×d)	Re-solution
DB1	Optical	96 × 96 (9 kpixels)	140 × 12	10 × 12	500 dpi
DB2	Optical	400 × 560 (224 kpixels)	140 × 12	10 × 12	569 dpi
DB3	Thermal sweeping	400 × 500 (200 kpixels)	140 × 12	10 × 12	500 dpi
DB4	SFinGe v3.0	288 × 384 (108 kpixels)	140 × 12	10 × 12	About 500 dpi

Each dataset in FVC2006 fingerprint database is 150 fingers wide and 12 enrolments per finger to make a total of 1,800 fingerprint images. There is also a partition of two disjoint subsets A and B in each dataset with each of subsets DB1-A, DB2-A, DB3-A and DB4-A containing the first 140 fingers (1,680 images) of DB1, DB2, DB3 and DB4, respectively while subsets DB1-B, DB2-B, DB3-B and DB4-B each contains the last 10 fingers (120 images) of DB1, DB2, DB3 and DB4, respectively.

4.2 System evaluation

During evaluation, the algorithms described in Refs.[3,21,22] were implemented for fingerprint enhancement, the algorithm described in Ref.[21] was implemented for minutiae extraction and the algorithms presented in Refs.[17,24] were implemented for core/delta point detection. Results of matching were classified into correct, false positive, false negative and mixed. With correct results, the reference fingerprint is correctly matched (matching score exceeded threshold) to one or more fingerprints from the same person while in the false positive, the reference fingerprint is matched to one or more fingerprints of another person.

In the false negative scenario, the reference fingerprint refused to match with any of the fingerprint in the database (while the database is inclusive of fingerprints from the same person as the reference fingerprint). Finally, with mixed results, there is no enough evidence to assign the reference fingerprint to any of the previous categories. Since more than one fingerprint is stored in the database for each of the 500 persons, ideally, the reference fingerprint is matched to several images of the same source. For mixed cases, the list of matches contains fingerprints from other sources. These were resolved by using a "majority" rule in which the reference fingerprint is assigned to the individual with the highest number of fingerprints in the list of matches.[4] An experimentally chosen threshold of 70% for minutiae-core point distance matching was used and Table 3 and Table 4 show the results of matching with 5 and 10 randomly selected and stored images of the same finger in the two local databases. A total of 2,500 and 5,000 fingerprints respectively were involved in each case.

Table 3. Results for database containing 5 fingerprints images obtained from the same person

Trial	Uareu				SecuGen			
	Correct	**False Positive**	**False negative**	**Mixed**	**Correct**	**False Positive**	**False negative**	**Mixed**
1	93.06	0	6.94	0	91.23	0	8.77	0
2	90.51	0	9.49	0	95.23	0	4.77	0
3	99.02	0	0.98	0	98.65	0	1.35	0
4	94.58	0	5.42	0	94.65	0	5.35	0
5	96.74	0	3.26	0	95.35	0	4.65	0
6	98.67	0	1.33	0	97.32	0	2.68	0
7	89.39	0	10.61	0	92.47	0	7.53	0
8	92.69	0	7.31	0	88.85	0	11.15	0
9	98.67	0	1.33	0	95.56	0	4.44	0
10	90.53	0	9.47	0	90.78	0	9.22	0
Average	94.39	0	5.61	0	94.01	0	5.99	0

Table 4. Results for database containing 10 fingerprints images obtained from the same person

Trial	Uareu				SecuGen			
	Correct	**False positive**	**False negative**	**Mixed**	**Correct**	**False positive**	**False negative**	**Mixed**
1	98.07	0	1.84	0.09	89.58	0	7.81	2.61
2	92.65	0	7.35	0	93.95	0	4.47	1.58
3	95.87	0	4.13	0	91.09	0	8.91	0
4	93.81	0	5.26	0.95	90.58	0	9.02	0
5	97.49	0	2.51	0	96.01	0	2.42	1.57
6	97.01	0	2.09	0	92.28	0	7.72	0
7	92.42	0	7.58	0	94.39	0	5.61	0
8	89.08	0	8.90	2.02	91.03	0	8.28	0.69
9	93.72	0	4.87	1.14	97.09	0	2.91	0
10	95.31	0	5.69	0	89.96	0	10.04	0
Average	94.54	0	5.02	0.11	92.64	0	6.72	0.64

The results show that accurate matching is not dependent on the instrument (scanner) used for the enrolment of the fingerprints. It is also revealed that the average values obtained for Correct and False Negative in the two Tables are relatively close. This is an indication that increasing the number of prints does not render any great impact on the matching results. It implied, therefore, that the matching results are only affected by the quality of the images, which in these cases is fairly uniform. The recorded values of Zero for False Positive in all the trials indicate no cases of false match while the recorded False Negative values indicate the failure to match rate of the algorithm in the two cases.

The four datasets in FVC2006 fingerprint database show significant variation in size and quality. The experiments conducted on them therefore provided the basis for the evaluation of the performance level of the algorithm under different conditions of images. Figures 10-13 present the experimental results for images in each of the subsets of datasets DB1, DB2, DB3 and DB4 respectively. Each of subset DB1-A, DB2-A, DB3-A and DB4-A consists of 1,400 fingerprints obtained from 10 randomly selected images from each of 140 fingers while each of subsets DB1-B, DB2-B, DB3-B and DB4-B contained 100 images derived from 10 randomly selected images from 10 fingers.

The histogram of Figure 10 was based on the percentage values obtained from the correct matching (matching score exceeded the threshold) of each image with one or more images in its subset. Figure 11 was also derived from the false negative percentage values that arose from the failure of an image to match with any of the fingerprints in its subgroup. Figures 12 and 13 were also derived in similar fashion with Figures 10 and 11, respectively. Zero False Positive values were recorded for all the trials with very few instances of mixed matching. This indicates genuine identification of fingerprints that were not enrolled from the same finger. However, the values recorded for Correct and False Negative exhibit noticeable differences which are attributed to the significant variation in the quality of the images. The higher the Average Correct Matching, the lower the Average False Negative and vice versa resulting in indirect relationship between the two. The least Average Correct matching of 78.94% (see Figure 10) and 89.38% (see Figure 12) were recorded for 1,400 and 100 randomly selected images in subsets DB4-A and DB4-B respectively.

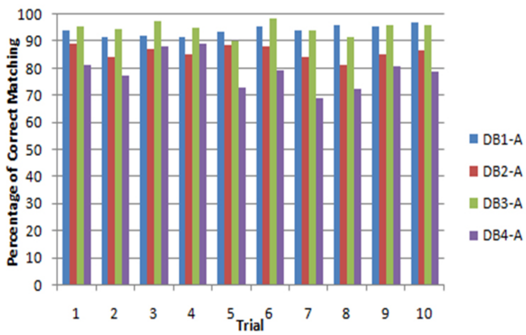

Figure 10. Correct matching based on 10 randomly selected fingerprint images of each of 140 persons

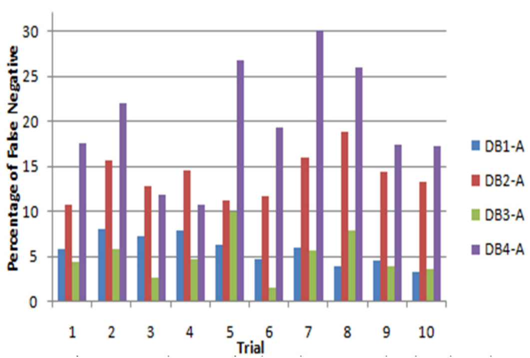

Figure 11. False negative based on 10 randomly selected fingerprint images of each of 140 persons

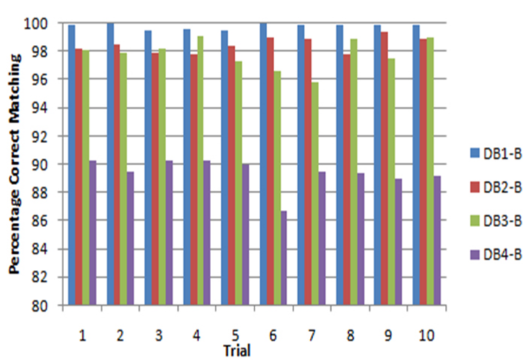

Figure 12. Correct matching based on 10 randomly selected fingerprint images of each of 100 persons

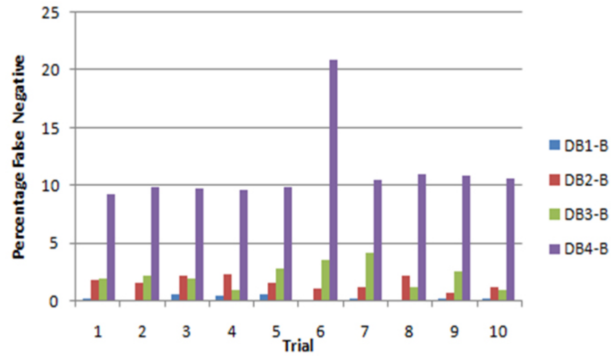

Figure 13. False Negative based on 10 randomly selected fingerprint images of each of 100 persons

Visual inspection of the images in the four datasets show that in comparison to others, dataset DB4 consists of images with poorest contrast and ridge connections as well as great ridge orientation imbalances among images from the same finger. It is therefore evident that the performance of the algorithm diminishes with reduction in the quality of fingerprint images. The quality and orientation differences caused great imbalance in the number of extracted minutiae and the relative position of the core and the minutiae points in images from same finger. This also led to great disparities in distances between the minutiae and core points. Typical examples of fingerprints of the same person that exhibit these problems are shown in Figure 14 with their unequal and uncorrelated core and minutiae points extractions. The extractions were based on the algorithms presented in Section 2.

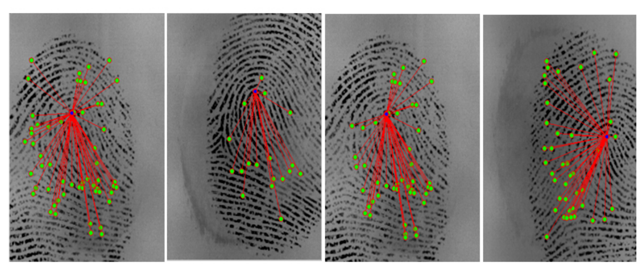

Figure 14. Same source fingerprints with different minutiae and core coordinate points

The ROC results obtained for the four datasets of FVC2006 fingerprint database-based matching were compared with the results from the implementation of the algorithms proposed in Refs.[12,28] The comparisons are shown in Figure 15 with best performance for the SMP algorithm. Each ROC curve depicts the plot of the correct match rate against false positive rate for all possible thresholds and measures the overall performance of the system.

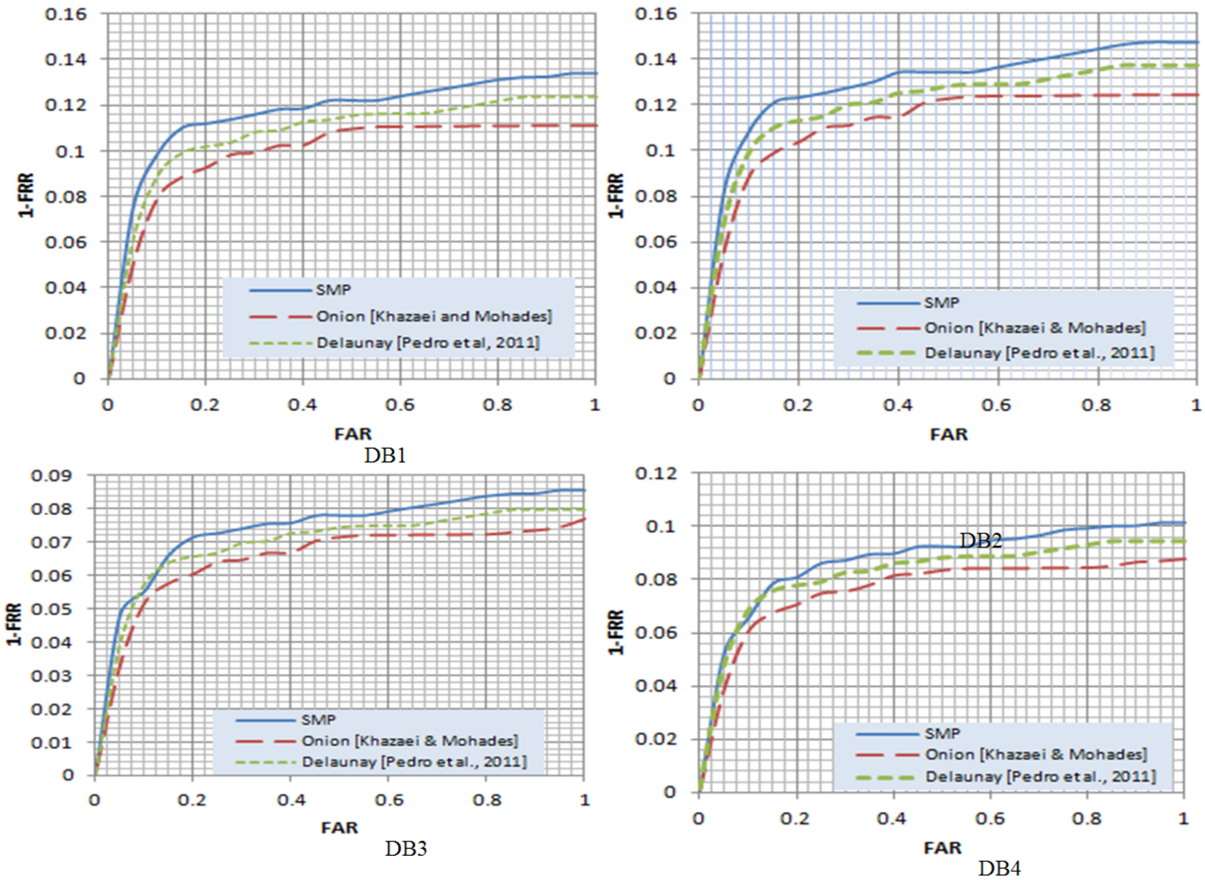

Figure 15. ROC of the new and some recent algorithms on FVC2006 datasets

The response time of the SMP algorithm depends on the template database. If a match is found on the template fingerprint database, then the average response time is in a few seconds (usually, 1-1.86). However, if a match is not found, the response time is much higher (double or even triple).

5. Conclusion

The study has proposed a singular-minutia point relationship-based algorithm for addressing the problem of alignment of two minutiae feature vectors in fingerprint matching. Results from the implementation of the algorithm on locally obtained fingerprints and the four datasets of FVC2006 fingerprint database show relevance and meaningfulness. It is revealed that the recording instrument (scanner) has no major impact on fingerprint matching and that matching results are only affected by the quality of the images, and not the number of templates in the fingerprints database. The ROC results obtained for FVC2006 fingerprint database by SMP and the algorithms proposed in Refs.[12,28] show best performance for the SMP algorithm. The SMP algorithm uses the minutiae and singular points locations for matching. However, additional information such as local orientation can improve the results. Increasing the threshold for the number of matched minutiae is also another way of performance improvement but this will undoubtedly raise the number of false negatives. Future researches will therefore focus on exploring these options for optimizing the performances of the algorithm.

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