Minutiae Inter-Distance Measure for Fingerprint Matching

Gabriel Babatunde Iwasokun, Oluwole Charles Akinyokun, and Olumuyiwa Johnson Dehinbo

Abstract**—**Biometrics has featured prominently for human verification and identification and fingerprint has remained the dominant one. This dominance is established by the continuous emergence of different forms of Automated Fingerprint Identification Systems (AFIS). In the course of performing human verification and identification, an AFIS conducts a lot of activities including fingerprint enrolment, creation of profile database and enhancement. Others are minutiae extraction, pattern recognition and matching, error detection and correction and decision making. In this paper, a minutiae-based algorithm for fingerprint pattern recognition and matching is proposed. The algorithm uses the distance between the minutiae and core points to determine the pattern matching scores for fingerprint images. Experiments were conducted using FVC2002 fingerprint database comprising four datasets of images of different sources and qualities. False Acceptance Rate (FAR), False Rejection Rate (FRR) and the Average Matching Time (AMT) were generated and used for measuring the performance of the proposed algorithm. Results showed that the algorithm is very adequate for distinguishing fingerprints obtained from different sources. It is also revealed that the ability of the algorithm to match images from same source is heavenly dependent on the qualities of such images**.**

Keywords**—**Minutiae, Pattern Matching, FRR, FAR, FVC2002, Fingerprint.

I. INTRODUCTION

FINGERPRINT is an impression of the friction ridges of all or any part of the finger. It is a deposit of minute ridges and valleys formed when a finger touches a surface. Facts exist that the ridges of fingers never change throughout lifetime no matter what happens. Even in case of injury or mutilation, they reappear within a short period. The five commonly found fingerprint ridge patterns are arch, tented arch, left loop, right loop and whorl (Figure 1) [1 - 6].

Fingerprint has proved to be a very reliable human identification and verification index and has enjoyed superiority over all other biometrics including nose, iris, voice, face, and signature [7]. The uniqueness of the ridges makes it immutable and therefore serves a strong mark for identity.

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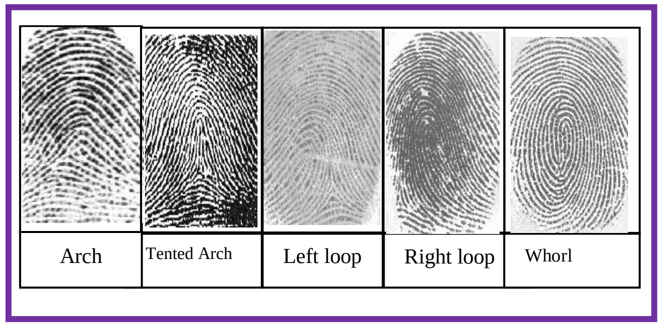

Fig. 1 Types of thumbprints patterns

Fingerprint pattern matching is carried out when the need for ascertaining the exactness or variations among fingerprint images arises and it involves the generation of matching scores [8]. When fingerprints from the same finger are involved, the matching scores are expectedly high and low for fingerprints from different fingers. Fingerprint matching faces a number of challenges including large intra-class variations (variations in fingerprint images of the same finger) and large interclass similarity (similarity between fingerprint images from different fingers). Intra-class variations are caused by finger pressure and placement (rotation, translation) and contact area with respect to the sensor and condition of the finger such as skin dryness and cuts. On the other hand, interclass similarity can be large due to limited number of fingerprint patterns; namely arch, loop, and whorl [9].

In this study, an algorithm for fingerprint pattern matching based on distance measurement between minutiae and core point is developed. Section 2 presents the review of some related works. Section 3 presents the proposed fingerprint pattern matching algorithm. A case study of the benchmark FVS2002 fingerprints is presented in Section 4 while Section 5 focuses on the conclusion drawn.

II. LITERATURE REVIEW

A. Various Techniques for Matching Fingerprints

Various techniques have been formulated by different authors for the matching of fingerprints. Among them is the minutiae based technique that has attracted interest from different research groups. This technique is widely adopted because fingerprint minutiae are the most unique, durable and reliable features. Minutiae based fingerprint matching algorithm is designed for solving problems of correspondence and similarity computation. Each minutia is assigned texture-based and minutiae-based descriptors for the correspondence

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problem in [10]. An alignment-based greedy matching algorithm is then used to establish the correspondences between minutiae.

The authors in [11] proposed a novel algorithm based on global comprehensive similarity with three phases. Firstly, a minutia-simplex that contains a pair of minutiae as well as their associated textures was built to describe the Euclidean space-based relative features among minutiae. Its transformation-variant and invariant relative features were employed for the comprehensive similarity measurement and parameter estimation respectively. Secondly, the ridge-based nearest neighborhood among minutiae was used to represent the ridge-based relative features among minutiae. With this approach, minutiae were grouped according to their affinity with a ridge. Finally, the relationship between transformation and the comprehensive similarity between two fingerprints was modeled in terms of histogram for initial parameter estimation.

While tremendous progress has been made in plain and rolled fingerprint matching, latent fingerprint matching continues to be a difficult problem. Poor quality of ridge impressions, small finger area, and large nonlinear distortion are the main difficulties in latent fingerprint matching compared to plain or rolled fingerprint matching. A system for matching latent fingerprints found at crime scenes to rolled fingerprints enrolled in law enforcement databases is proposed in [12]. Extended features, including singularity, ridge quality map, ridge flow map, ridge wavelength map, and skeleton were used. The matching module consists of minutiae, orientation field and skeleton matching. The importance of various extended features was studied and the experimental results indicate that singularity, ridge quality map and ridge flow map are the most effective features in improving the matching accuracy.

The authors in [13] proposed a filter-based algorithm that uses a bank of Gabor filters to capture both local and global details in a fingerprint as a compact fixed length FingerCode. Fingerprint matching was based on the Euclidean distance between the two corresponding FingerCodes. The experimental results show that the algorithm was extremely fast with high verification accuracy which was only marginally inferior to the best results of minutiae-based algorithms presented in [14].

Minutiae-based pattern matching is mostly used because forensic examiners have successfully relied on minutiae to match fingerprints for a long period of time. Minutiae-based representation is storage efficient and expert testimony about suspect identity based on mated minutiae is admissible in courts of law [9]. The latest trend in minutiae matching is to use local minutiae structures to quickly find a permissible alignment between two fingerprints and then consolidate the local matching results at a global level. This kind of matching algorithm typically consists of the steps conceptualized in Figure 2.

The first step of the algorithm is the fingerprint enrolment [9]. The enrolled fingerprint is enhanced for smooth and speedy extraction of minutiae.

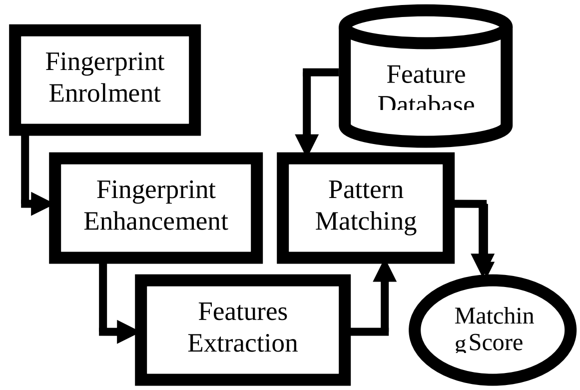

Fig. 2 A typical fingerprint pattern matching steps

B. *Enhancement of Fingerprint Matching*

Enhancement involves ridge segmentation, normalization, orientation estimation, frequency estimation, filtering, binarization and thinning [15-17]. Algorithms for the extraction of minutiae points from thinned fingerprint images have been proposed in [8, 15, 16, 18]. A number of these algorithms use the 8-nearest neighbors approach to extract a ridge point as a bifurcation, ending, isolated, continuing or crossing point [6]. During feature matching, a pairwise similarity between minutiae sets of two fingerprints is computed. This is done by comparing minutiae descriptors that are invariant to rotation, size and translation [9].

III. Proposed Fingerprint Matching Algorithm

A new method for generating fingerprints matching scores using the spatial parameters that exist between fingerprint minutiae points is proposed. The motivation behind the algorithm is the need to address the matching problems due to image ridge orientation and size variations. The algorithm takes advantage of the fact that the relative distance to the core point from each minutia point does not change irrespective of the image directional flow for a given image size. The core point is the point of maximum turning at which the gradient is zero. The core points A and B shown in Figure 3 are the points of maximum turning of the ridge structures in the two images. They are also the points where the directional fields experience total orientation changes [17, 19]. Among the common feature points that uniquely describe a fingerprint image are bifurcations and ridge endings [8, 16], which are represented by circles and squares respectively in Figure 4. The core points are represented with the thick diamonds.

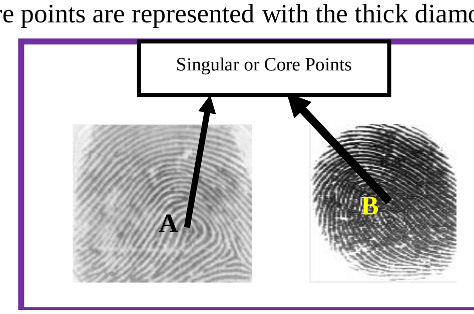

Fig. 3 Fingerprint images and their core points

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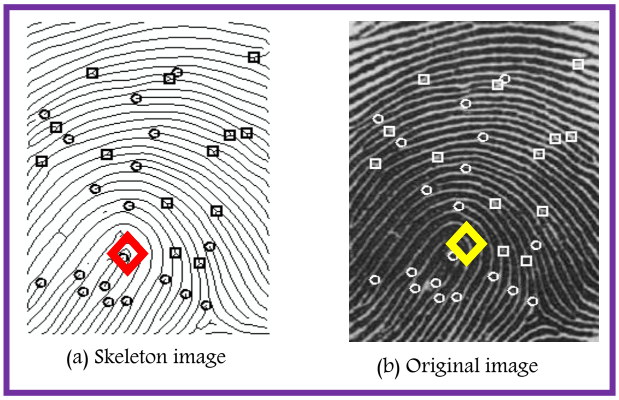

Fig. 4 Feature points for skeleton and original images

Figure 5 illustrates typical interconnecting lines between nine (9) minutiae points labeled A, B, C, D, E, F, G, H and I and the core point O in a region of an image. The connecting lines are in different directions with lengths proportionate to the distances from point O to the minutiae points.

The procedure for the proposed algorithm is in the following phases:

a. Obtain the core point using the following procedure [20].

- Divide the fingerprint image, I, into blocks of size N x N.
- Compute the orientation estimate for the center pixel A(i,j) of each block.
- Compute the sine component in radian of each estimate using sin(*A*(i , j))

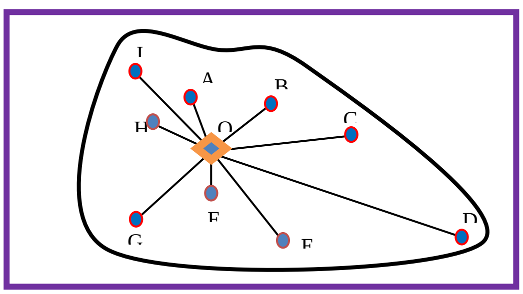

Fig. 5 Interconnecting lines between feature and core points

A perfectly horizontal ridge has a sine component of 0 while vertical ridge has a sin component of 1. Due to the discontinuity property, the sine component value always changes abruptly from 0 to 1 or vice versa at the core point. In view of this, the following additional operations are performed:

- Initialize a 2 dimensional array B(i,j) and set all its entries to 0.
- Scan the sine components map in a top-to-bottom, left-to right manner.

For each sine component

$$B(i,j)=Sine(A(i,j)), \tag{1}$$

If B(i, j) < the threshold, B(i - 1, j) > p / 2 and B(i + 1, j) > p / 2 then:

Compute the difference D between the sine components for block with center at pixel (i,,j) and another block with center pixel at (k,l) using the formula:

$$D = Sin(i,j) - Sin(k,l) \tag{2}$$

C(i,j) entry is used to compute the continuity of a possible reference candidate point and is defined as:

$$C(i,j) = \begin{cases} 1; & \text{if } i == 1 \\ B(i-1,j-1) + B(i-1,j) + B(i-1,j+1); & \text{otherwise} \end{cases} \tag{3}$$

End if

b. Obtain the x and y coordinates for all the true bifurcations and ridge endings in the thinned image. The Crossing Number (CN) value for a candidate ridge ending and bifurcation is obtained according to the formula [8, 18]:

$$CN = \sum_{i=0}^{7} |N_{i+2} - N_{i+1}|, \qquad N_9 = N_1 \tag{4}$$

N_1, N_2, …, N_8 denote the 8 neighbours of the candidate minutia point in its 3 x 3 neigbourhood scanned in clockwise direction as follows:

N_2	N_3	N_4
N_1	N	N_5
N_8	N_7	N_6

As shown in Figure 6, a ridge pixel with CN value of 2 corresponds to a ridge ending and a CN value of 6 corresponds to a bifurcation.

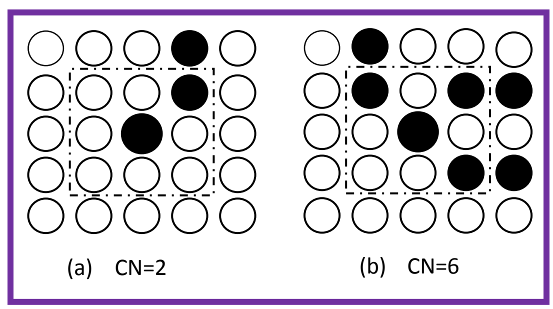

Fig. 6 CN values for ridge ending and bifurcation points

To ensure the extraction of valid minutiae only, a validation algorithm proposed in [8] is implemented. The algorithm tests the validity of each candidate minutia point by scanning the skeleton image and examines its local neighborhood. Firstly, an image *M* of size *W x W* centered on the candidate minutia point in the skeleton image is created. Secondly, the central pixel of *M* is labeled with a value of 2 and the rest of the pixels in *M* are initialized to value of zero. Subsequent steps depend on whether the candidate minutia point is a ridge ending or a bifurcation. For a candidate bifurcation point:

- Examine the 3 x 3 neighborhood in a clockwise direction and label the three connecting pixels with the value of 1.

TABLE I
DETAILS OF FVC2002 FINGERPRINT DATABASE

Data -base	Sensor Type	Image size	Number	Resolution
DB1	Optical Sensor	388 × 374 (142 Kpixels)	100 × 8	500 dpi
DB2	Optical Sensor	296 × 560 (162 Kpixels)	100 × 8	569 dpi
DB3	Capacitive Sensor	300 × 300 (88 Kpixels)	100 × 8	500 dpi
DB4	SFinGe v2.51	288 × 384 (108 Kpixels)	100 × 8	About 500 dpi

- Also label with 1, the three ridge pixels that are linked to the three connected pixels.
- Count in a clockwise direction, the number of transitions from 0 to 1 (T_{01}) along the border of image M. If T_{01} = 3, then the candidate minutia point is validated as a true bifurcation.

For a candidate ridge ending point:

- In the image M, Label with a value of 1 all the pixels in the 3 x 3 neighbourhood of candidate point.
- Count in a clockwise direction, the number of 0 to 1 transitions (T_{01}) along the border of the image. If T_{01} = 1, then the candidate minutia point is validated as a true ridge ending.

c. The distance, λ_i between the i[th] minutia point $P_i(a_i,b_i)$ and the core point $M(\rho,\sigma)$ is obtained from:

$$\lambda_{\mathrm{i}} = ((a_i - \rho)^2 + (b_i - \sigma)^2)^{0.5} \qquad (5)$$

d. Image K is matched with image L to obtain the degree of closeness, E_c by using the formula:

$$E_c = \sum_{i=1}^{s} (|G(i) - H(i)|) * \{G(i)\}^{-1} \qquad (6)$$

s is the smaller of the respective number of feature points in the two images, G(i) and H(i) represent the distance between the i[th] minutia point and the core points in K and L respectively.

e. The correlation coefficient, S between K and L, is computed to give the pattern matching score by using the formula:

$$S = (1 - E_c) * 10^{-2} \qquad (7)$$

From Equation (7), E_c = 0 for exact or same images and, consequently, the matching score is S = 1.

IV. EXPERIMENTAL RESULTS

The implementation of the proposed fingerprint matching algorithm was carried out using Matlab version 7.6 on Ms-Window Vista Home Basic Operating System. The experiments were performed on a Pentium 4 – 2.10 GHz processor with 1.00GB of RAM. The experiments were conducted for the analysis of the performance of the proposed algorithm under different image qualities. The experiments also served the basis for the generation of metric values that are relevant for the comparison of the obtained results with those from related works. Case study of fingerprint obtained from FVC2002 Fingerprint Database was carried out. The database was jointly produced by The Biometric Systems Laboratory, Bologna, Pattern Recognition and Image Processing Laboratory, Michigan and the Biometric Test Center, San Jose, United States of America. It consists of four datasets DB1, DB2, DB3 and DB4 and its summary is presented in Table 1 [21].

Each of the four datasets contains 80 images that differ in qualities. Each dataset is made up of 5 fingerprints from 16 different fingers. The first two datasets were acquired using optical fingerprint readers. The third and fourth datasets were acquired using capacitive fingerprint readers and computer software assistance respectively. False Rejection Rate (FRR), False Acceptance Rate (FAR) and Average Matching Time (AMT) were the indicators measured. These indicators were chosen because they are among the commonest indicators used for measuring the performance of any biometric pattern matching systems [9]. FRR is the rate of occurrence of a scenario of two fingerprints from same finger failing to match (the matching score falling below the threshold). On the other hand, FAR is the rate of occurrence of a scenario of two fingerprints from different fingers found to match (matching score exceeding the threshold). For each dataset, FRR was measured by matching fingerprints obtained from the same finger while FAR was measured through matching each fingerprint image of each finger with all fingerprints from the other fingers.

The obtained results revealed that some factors affect the indicators. For instance, FRR and FAR results were greatly affected by the nature and quality of the images. The results obtained at threshold value for the first two datasets are shown in Table 2 and Table 3 respectively.

TABLE II
FAR AND FRR VALUES FOR DATASET DB1

Statistics	Value (%)
FAR	0
FRR	22.23

These results revealed that for images obtained using optical fingerprint reader, the proposed algorithm produced an FAR of 0%. This reveals the ability of the algorithm to identify in the two datasets, fingerprint images obtained from different fingers. However, the obtained FRR values of 22.23% and 19.85% present the level to which the algorithm failed to match fingerprint from the same finger. Some factors which include variation in pressure, rotation, translation and contact area during enrolment have been said to be responsible for this failure [9]. These factors forced images enrolled from the same finger to show differences in quality, contrast and noise level. Consequently, different matching scores are obtained for different pairs of fingerprints from same finger. The obtained FAR and FRR values obtained for the third dataset are presented in Table 4. The results show that for this dataset, the proposed algorithm produced an FAR of 0%.

TABLE III
FAR AND FRR VALUES FOR DATASET DB2

Statistics	Value (%)
FAR	0
FRR	19.85

TABLE IV
FAR AND FRR VALUES FOR DATASET DB3

Statistics	Value (%)
FAR	0
FRR	14.51

This reveals that the algorithm is also able to identify fingerprint images captured from different fingers using capacitive fingerprint reader. The obtained FRR value of 14.51% reveals the failure rate of the algorithm when matching fingerprint images enrolled from same finger. This lowest failure rate when compared to values for Datasets DB1 and DB2 is attributed to improved image quality for Dataset DB3. Visual inspection of fingerprint images in dataset DB3 reveals significant reduction in sizes and greater clarity leading to better enhancement and extraction of predominantly true minutiae points. The higher FRR values in the first two datasets imply that the enhancement process is more adversely affected by noise and artifacts. Artifacts are foreign ridges and valleys introduced inform of cross over, hole or spike structures into the image during the enhancement process [8]. Noise and artifacts mislead the feature extraction algorithm into the extraction of different number of false minutiae (ridge ending and bifurcation) across images from same finger thereby causing unequal size in minutiae set which result in higher FRR rate. Dataset DB4's FAR and FRR values are shown in Table 5. These values equally confirmed the identification of fingerprint images captured from different fingers using computer aids. However, the obtained FRR value of 16.47% revealed the failure rate of the algorithm when matching images from the same finger.

TABLE V
FAR AND FRR VALUES FOR DATASET DB4

Statistics	Value (%)
FAR	0
FRR	15.47

Visual inspection of the 80 fingerprint images contained in the dataset DB4 reveals better connection between the ridges when compared with images in datasets DB1 and DB2. This is why dataset DB4's FRR value is lower than what obtained for datasets DB1 and DB2. However, when compared with the FRR value for dataset DB3, the higher FRR recorded for dataset DB4 indicates that the images in dataset DB3 are better in terms of ridge connections and qualities. This also implies that gaps across the ridges in dataset DB4 show greater adversity on the extraction of various numbers of false minutiae. The recorded FRR value of 16.47% therefore indicates that these false minutiae points affected negatively on dataset DB4 than on dataset DB3.

The trend of the FRR values of the four datasets is represented on the straight-line graph shown in the column chart shown in Figure 7. Figure 7 shows that the FRR values for the four datasets decrease in the order 22.23, 19.85, 16.47 and 14.51 for datasets DB1, DB2, DB4 and DB3 respectively. This means that in term of quality, Dataset DB3 has the best set of images while those in dataset DB1 are the worst. In the overall, for the four datasets, the proposed pattern matching algorithm identified fingerprints from different fingers by returning an average FAR of 0%. An average FRR value of 18.26% is also recorded as the extent to which the algorithm failed to match all fingerprint images from the same finger. The average matching times in seconds and their trend for FRR and FAR for the four datasets are presented in Table 6 and the column chart of Figure 8 respectively.

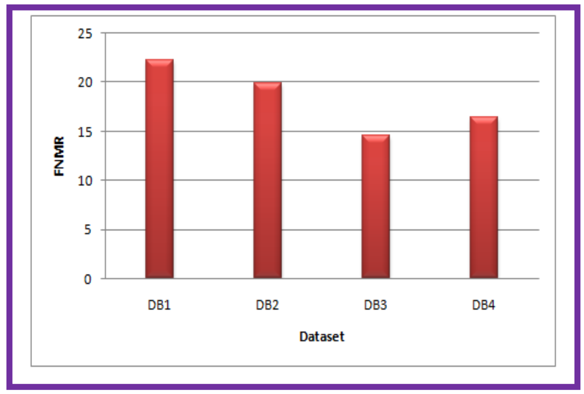

Fig. 7 Column chart of the FRR values for the four datasets

TABLE VI
AVERAGE MATCHING TIME FOR THE FOUR DATASETS

Datasets	Average Matching Time (secs)	
	FAR	FRR
DB1	1.16	1.61
DB2	0.91	1.27
DB3	0.79	0.93
DB4	0.86	0.89

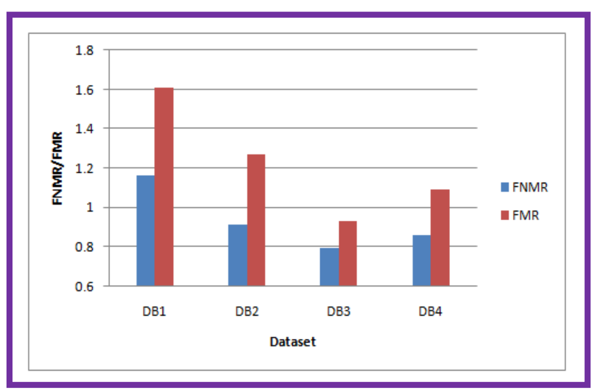

Fig. 8 Column chart of the FRR matching completion for the four datasets

Dataset DB3 has the lowest FRR average matching time of 0.79 second followed by DB4, DB2 and DB1 with FRR average matching time of 0.86, 0.91 and 1.16 second respectively. DB4 records the lowest FAR average matching time of 0.89 seconds followed by DB3, DB2 and DB1 with average FAR matching time of 0.93, 1.27 and 1.61 seconds respectively. The lowest FRR average matching rate for dataset DB3 implies that same finger images in the dataset has fewest numbers of minutiae points when compared to other datasets and consequently, smallest number of computations. Similarly, the highest FRR average matching time recorded for dataset DB1 indicates highest number of minutiae points in same finger images and consequently, the highest number of computations. These explanations also apply as appropriate for the FAR values.

Table VII presents the FRR and FAR values for four different algorithms. The algorithms presented in [22-24] were selected for comparison because they are among the most recent and just like the current study, they used FVC2002 fingerprint database for their system evaluations. In Table 7, the original values obtained by the authors in [22, 24] are presented.

However, we implemented the algorithm proposed in [24] under the conditions of experiments in this research to obtain the stated values. The superior performance of the proposed algorithm over the other algorithms is clearly exhibited with its lowest FRR values for all the datasets. In addition, it is the only algorithm with an FAR value of zero for all the datasets. The column charts of Figures 9 and 10 are based on values presented in Table VII and they illustrate the performance trend of the four algorithms. Table VIII presents the obtained FRR and FAR computations time in seconds in [23, 24] and the current study.

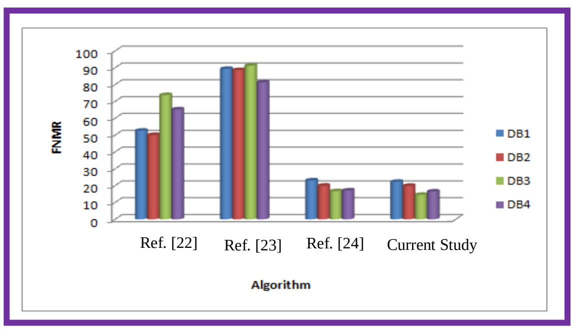

Fig. 9 Colum Chart of FRR values for different fingerprint

TABLE VII

FAR AND FRR FOR DIFFERENT ALGORITHMS

	Ref. [22]		Ref. [23]		Ref. [24]		Current Study	
Data	FRR	FAR	FRR	FAR	FRR	FAR	FRR	FAR
DB1	52.58	0	89.3	1.7	23.07	0	22.23	0
DB2	50.03	0	88.6	3.7	19.91	0	19.85	0
DB3	73.75	0	91.2	2.4	16.68	0	14.51	0
DB4	65.24	.015	81.3	0.9	17.09	0.01	16.47	0

TABLE VIII

MATCHING TIME IN SECONDS FOR DIFFERENT ALGORITHMS

	Ref. [23]		Ref. [24]		Current Study	
Dataset	FRR	FAR	FRR	FAR	FRR	FAR
DB1	2	1.7	1.31	1.84	1.16	1.61
DB2	4	3.7	1.04	1.32	0.91	1.27
DB3	2	2.4	1.01	1.39	0.79	0.93
DB4	3	0.9	0.91	1.23	0.86	0.89

We also implemented the original algorithm proposed in [24] under equal condition of experiments to obtain the stated values. For all the datasets, the proposed algorithm exhibited lower computation time, which confirms its superiority in term of operational speed as shown in the column charts of Figures 11 and 12.

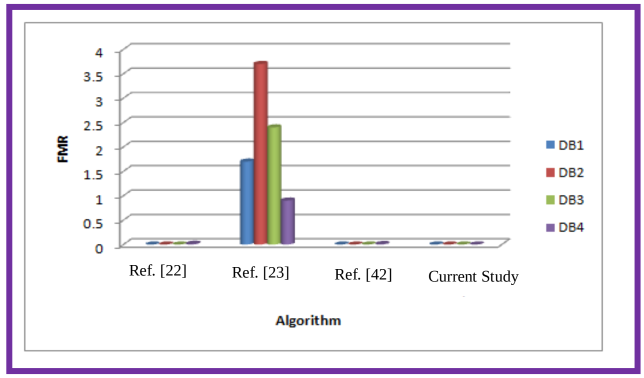

Fig. 10 Colum Chart of FAR values for different fingerprint matching algorithms

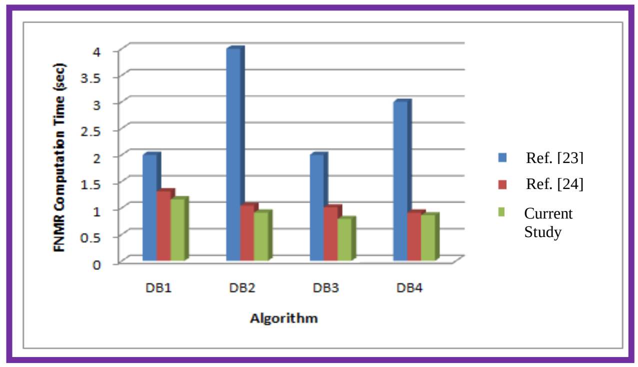

Fig. 11 Colum Chart of Computation time for FRR values for different fingerprint matching algorithms

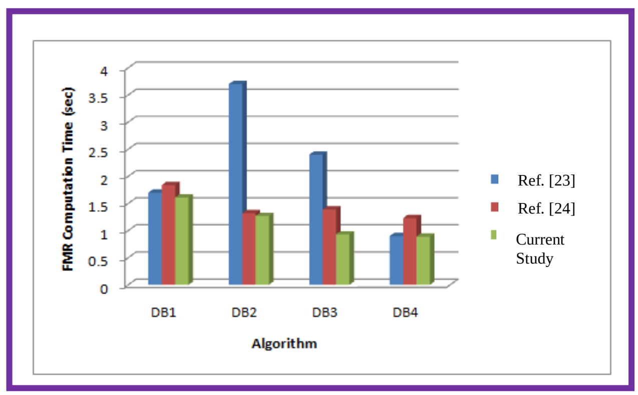

Fig. 12 Colum Chart of Computation time for FAR values for different fingerprint matching algorithms

Figure 13 shows the column chart of the average FRR based on the data presented in Tables 7 for four different algorithms over the four datasets. Similarly, Figure 14 represents the column chart of the average FRR and FAR computation times based on data presented in Table 8 for the three algorithms. This reveals superior performance of the proposed algorithm having recorded smallest heights in both cases.

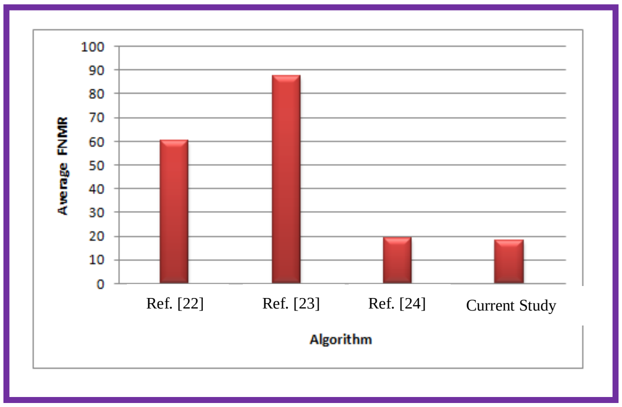

Fig. 13 Colum Chart of Average FRR values for different fingerprint matching algorithms over the four datasets

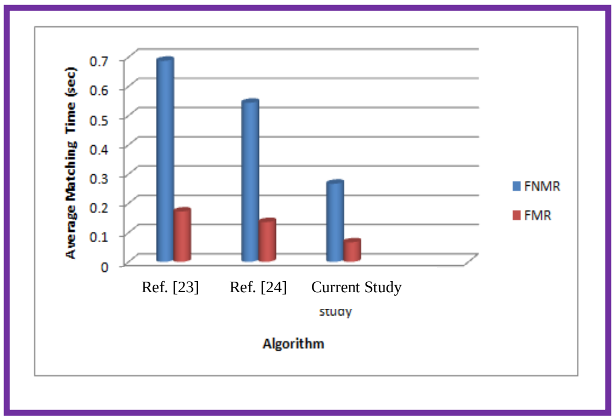

Fig. 14 Colum Chart of Average Computation time for FRR and FAR values for different fingerprint matching algorithms over the four datasets

V. CONCLUSION AND FUTURE WORKS

The implementation of a new fingerprint pattern matching algorithm is presented using the relative distances between the minutiae and the core points. The algorithm hinged on the premise that irrespective of image orientation, each minutia point maintains constant distance with the core point for a given image size. Results obtained showed effectiveness of the algorithm in distinguishing fingerprints from different sources with average FAR of 0%. However, the ability to match images from same source depends on the qualities of images. Since corruption levels vary across used datasets, the algorithm yielded different FRR values. The first dataset is mostly affected with FRR values of 22.23% while the third dataset is least affected with FRR value of 14.51%.

The same order of performance was recorded for the FRR and the average matching time over the datasets. A comparative review of the obtained FRR, FAR and the computation time values with what obtained for some recently formulated algorithms over the same datasets revealed best performance for the proposed algorithm. Future research direction aims at the optimization of the proposed algorithm.

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