INTERNATIONAL JOURNAL OF INFORMATION SECURITY SCIENCE
S.O. Ogunlana et al., Vol.10, No.3, pp.75-85

Fingerprint Individuality Model Based on Pattern Type and Singular Point Attributes

Samuel Olutayo Ogunlana[1], Gabriel Babatunde Iwasokun[2], Olatubosun Olabode[3]

[1]Information Communication Technology and Application Centre, Adekunle Ajasin University, Akungba Akoko, Nigera

[2] Department of Software Engineering, Federal University of Technology, Akure, Nigeria

[3] Department of Information Systems, Federal University of Technology, Akure, Nigeria

Corresponding Author:gbiwasokun@futa.edu.ng

Research Paper Received:17.02.2020 Revised: 03.09.2020 Accepted: 15.09.2021

Abstract—This paper presents a singular point and pattern type model for the investigation of fingerprint individuality. The extraction of the singular point is based on the modified Poincare method while the determination of the pattern type is based on plane geometry and the attributes of the singular point on the quadrants. The experimental study involved Matlab version R2018a as the frontend while Microsoft Access Relational Database Management System served the backend. Benchmarked FVC2002 fingerprint database which comprises four datasets from different sources and of varied types were used for the experimental study. The experimental study established the viability and the functionality of the model while results for average matching time, false non match rate and false match rate confirmed that the model is practically feasible as well as its suitability for use in Automated Fingerprint Identification System (AFIS)..

Keywords—Fingerprint, singular point, pattern type, FVC2002, individuality

1. Introduction

Fingerprint represents the pattern exhibited by the ridges and valleys of a finger. The ridges formed the dark and raised layers while the white and lowered portions are the valleys [1]. Fingerprint is noted for permanence and uniqueness and remains a token for identification due to its reliability, immutability and individuality [2],[3]. The uniqueness of a fingerprint is quantified by its pattern type as well as feature and singular point characteristics. The commonest fingerprint features include ridge ending (termination), bifurcation, lake or enclosure, short ridge or independent ridge, point or island, spur and crossover. The existing fingerprint pattern types are left loop, right loop, double loop, whorl, arch and tented arch. A singular point is defined as a region where the ridge orientation field experiences discontinuities either through higher than normal ridge curvature or where the direction of the ridge changes rapidly resulting in zero gradient. It is classified into two types namely; core and delta points. The ridges experience maximum turning (change in orientation) at the core point while they experience a tri-directional change at the delta point ([4],[5],[6],[7]). The fingerprint individuality problem can be formulated based on the probability that any two individuals may have sufficiently similar fingerprints in a given target population. The probability is often based on the correspondence index between pattern type as well as the feature and singular points characteristics. The representation of fingerprint minutiae, which is exploited by forensic experts, has been demonstrated to be relatively stable and has been adopted by the majority of automatic fingerprint matching systems. The similarity figure is obtained from the correspondence metric between two minutiae set based on empirical and theoretical approaches. In the empirical approach, representative samples of fingerprints are collected and matched to establish their uniqueness with respect to the matcher. The theoretical approach to individuality estimation involves prototyping all realistic phenomenon affecting inter and intra-class pattern variations as a means of establishing the probability of false and true associations ([8],][9]). Current challenges militating against some of the existing algorithms or models for assessing fingerprint individuality include large intra class variability (which could be due to displacement, rotation, partial overlap, non-linear distortion, pressure, skin condition, noise and feature extraction error factors), inter class similarity and impression variability ([6],[10],[11],[12]). Galton, Henry and Balthazard, Osterburg, Stoney and Thornton, Roxburg, Amy,Trauring and Kingston models are some of the established fingerprint individuality models ([6],[8]). In [6], a generalized mixed model framework for assessing fingerprint individuality in the presence of varying image quality is proposed. The model failed to consider intra-class variations in multiple impression of a finger. The author in [4] presents a fingerprint pattern matching algorithm which addresses the matching problems due to variations in image ridge orientation and size. However, the algorithm does not incorporate pattern type features and requires high computational time. The authors in [?] also developed singular-minutiae point relationship-model for fingerprint matching. The algorithm does not incorporate local orientation feature coupled with increase in the threshold needed to improve its performance. For the enhancement of the prevailing fingerprint image augmentation approaches, the authors in [14] proposed a model to pact with various fingerprint images. The model is suitable for denoising, augmentation and improved classification rate but susceptible to parameter effect and computational complexity. The authors in [15] proposed models for enhancing fingerprint image, extract its minutiae and matching it with the templates. Results from the implementation showed some usefulness as well as its failure with large sample size fingerprint database coupled with no consideration for singular points. Findings had revealed that existing fingerprint individuality models experience various degrees of limitations which include low matching accuracy, computational complexities, diminishing performance with degraded images, lack of consideration for singular points and pattern types and failure to accommodate large datasets. The research being reported therefore developed a fingerprint individuality model that addresses these limitations.

2. Review of Some of the Existing Works

Several research works had been carried out by numerous authors leading to various models for establishing fingerprint individuality. These works had all placed emphasis on minutiae characteristics for their investigations without much emphasis on singular point and pattern type. A fingerprint pattern matching model that addresses the matching problems due to variations in image ridge orientation and size is proposed in [4]. The model does not incorporate pattern type and feature characteristics while experimentation revealled it is computationally expensive. In [6], a generalized mixed model framework for assessing fingerprint individuality in the presence of varying image quality is presented. The model gives no consideration to the intra-class variations in multiple impression of a finger. In [7], a minutiae-based fingerprint matching model is presented. The model establishes correspondence among input and stored minutiae patterns but underperforms with highly noising or degraded images. The model formulated in [8] relies on fingerprint image feature characteristics to establish individuality. Though the model recorded high recognition index, it is susceptible to minutiae error and discrepancies. The authors in[9]] proposed a statistical method for assessing the individuality of fingerprint. The model does not consider singular point features coupled with computational and time complexities of the algorithm. In [10], a singular-minutiae point relationship-based model is proposed for establishing fingerprint individuality. The model is however limited by its failure to incorporate local orientation features coupled with lack of experimentally proven threshold for establishing its performance. The authors in [16] presented a fingerprint individuality model that is based on minutiae characteristics. The model is able to operate with large sample size of database for categorization with respect to quality and diversities of fingerprints but gave no consideration to orientation variations coupled with failure to eliminate spurious features. A fingerprint individuality model based on ridge and pore features is proposed in [17]. The model extracts pore features and performs empirical estimation which is reported to be greatly affected by image quality as well as feature extraction and matching algorithms. The authors in [18] presented a circular string model that successfully identifies the locations and orientations of the characteristic features in the input fingerprint. Experimental results show that the performance of the model is dependent on the successful transformation of the minutiae features into 0s and 1s which is also a pre-condition for the circular string matching. For the prevention of restrictions on prevailing fingerprint image augmentation approaches, the authors in [14] presented a model to pact with various fingerprint images. The model uses wave atom for denoising, morphological operations for augmentation and Adaptive Genetic Neural Network (AGNN) for efficient classification of images. The model exhibited some promising results in tern of classification accuracy and precision but failed with dataset with high intra-class variations. The authors in [19] proposed a Transform-Minutiae Fusion (TMF) model for fingerprint recognition. The model seeks to solve the problem of accuracy via the fusion of transform and minutiae models. Wave atom transform was used for data smoothing while wavelet transform was used for feature extraction. The evaluation of the model on FVC 2002 dataset showed impressive results in terms of accuracy, though experienced computational complexities. A study on the impact of minutiae errors on latent fingerprint identification is presented in [20]. Experiments were conducted on the effect of ground-truth minutiae on latent fingerprints matching with findings revealing the impact levels of minutiae and how missing minutiae can bear significant negative impact on the identification accuracy and ranking of fingerprints. The study only determined the critical areas of a latent fingerprint in which missing minutiae could impact on matching, but failed to consider singular point, pattern type and minutiae combination as basis of investigating fingerprint individuality. A fingerprint enhancement, minutiae extraction and matching model is presented in [15]. The model uses Gabor filters for enhancement, Zhang Suen algorithms for feature extraction while it performs matching based on proof of identity through reference and template minutiae comparison. Its authenticity could not be established due to missing experimentation with large sample size database of fingerprints. The authors in [21] proposed a minutiae platform for fingerprint recognition. The platform comprises of modules for fingerprint image acquisition, pre-processing, feature extraction and matching. The experimental study of the platform is based on FVC2000 and FVC2002 fingerprint databases. Impressive figures are reported for FAR and FRR for good quality images in the databases while the reverse is the case for significantly corrupt fingerprint images.

3. Proposed Model

The proposed fingerprint individuality model exploits the attributes of fingerprint singular points for the investigation of fingerprint individuality. It is conceptualized in Figure 1 modules for fingerprint image enhancement, feature extraction, database of the extracted features and individuality investigation. While the enhancement of a fingerprint image is based on the model proposed in [22]. The detection of the singular point characteristics starts with dividing the fingerprint image into blocks of size S×S. The computation of the orientation (directional flow) for the center pixel A(i,j) of each block is then carried out and followed by the determination of the singular points for a pixel (i,j) based on a modified Poincare index

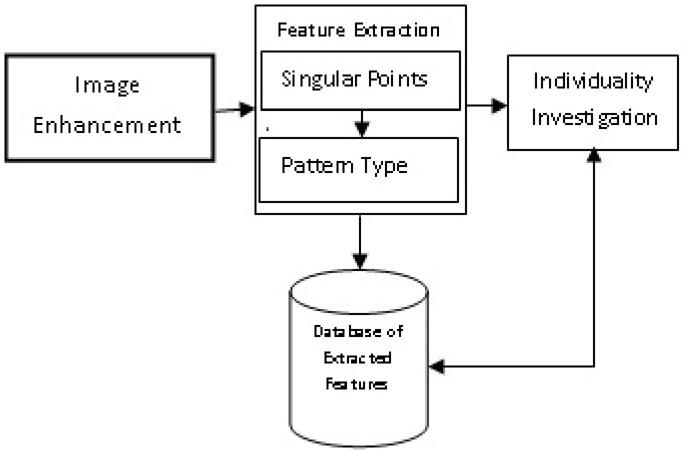


Fig. 1. The conceptualization of the fingerprint individuality model

method as follows [23]:

$$\mathbf{PC(i,j)} = \pi^{-1}\sum_{i=1}^{2}\beta_c \tag{1}$$

$$\beta_{\mathbf{c}} = \begin{cases} p(c)+\pi, & \text{if } p(c) \le -\frac{\pi}{2} \\ p(c), & \text{if } p(c) > -\frac{\pi}{2} \\ p(c)-\pi, & \text{otherwise.} \end{cases} \tag{2}$$

$$\mathbf{p(c)} = \mid O_{c+1} - O_c \mid, O_9 = O_1 \tag{3}$$

PC(i,j) represents singular point characteristics, (i,j) are orientation direction, β_c is the computed point characteristic, O_1, O_2,..., O_8 represent the orientations of the 3 x 3 neighbors of pixel (i,j). Based on these characteristics, the core point lies between -1 and -0.5 for PC(i,j) while the delta point is in the range 0.5 to -1.

The average core (or delta) is calculated for multiple core (or delta) in a circular region with radius of 8 pixels. Given that N cores (or delta) exist in an area, (u_i,v_i), i=1, 2,3,...,N) then, the average core (or delta) (u,v) is computed as follow:

$$\mathbf{u} = N^{-1}\sum_{i=1}^{N} u_i \tag{4}$$

$$\mathbf{v} = N^{-1}\sum_{i=1}^{N} v_i \tag{5}$$

u and v are average core and delta respectively, i=1, 2,...,N. N is the total number of core/delta in an area. The determination of the fingerprint pattern type begins with splinting the fingerprint image into four quadrants in a coordinate plane consisting of a horizontal axis (x-axis) and a vertical axis (y-axis). The two axes intercept at the origin, O which is taken as the point at which the image is evenly divided. The characteristics shared by the ordered pair within the four quadrants are presented in Table 1.

The arch, left loop, right loop and whorl pattern types are respectively determined as follow (illustrated in Figure 2):

Given a core/delta point with coordinate point P(x,y) on a plane with origin O(x_0,y_0), if $\bar{PO} \leq \rho$, where ρ is the threshold, then an arch pattern is detected (see Figure 2(a)).

If x< x_0 and y < y_0, then the singular point is on first quadrant and a right loop is detected (see Figure 2(b))

If x < x_0 and y>y_0, then the singular point is on fourth quadrant and a left loop is detected (see Figure 2(c)).

If dual core points (x_1,y_1) and (x_2,y_2) are detected, then a whorl pattern is detected (see Figure 2(d)).

TABLE 1
Characteristics shared by points in the four quadrants

Quadrant	Form	Description
1	(+,+)	Starting from the origin, go along the x-axis in a positive direction (right) and along the y-axis in a positive direction (up)
2	(-,-)	Starting from the origin, go along the x-axis in a positive direction (right) and along the y-axis in a negative direction (down)
3	(+,-)	Starting from the origin, go along the x-axis in a negative direction (left) and along the y-axis in a negative direction (down)
4	(-,+)	Starting from the origin, go along the x-axis in a negative direction (left) and along the y-axis in a positive direction (up)

The first, second, third and fourth quadrants of the coordinate plane are computed based on equations 6, 7, 8 and 9 respectively:

$$(1 < a\frac{x}{2})\&(\frac{y}{2} < b < y) \tag{6}$$

$$(\frac{x}{2} < a < x)\&(\frac{y}{2} < b < y) \tag{7}$$

$$(\frac{x}{2} < a < x)\&(1 < b < \frac{y}{2} \tag{8}$$

$$(1 < a < \frac{x}{2})\&(1 < b < \frac{y}{2}) \tag{9}$$

a and b are the coordinates of the core points, x and y are the row and column dimensions of the fingerprint image. Obtaining a different

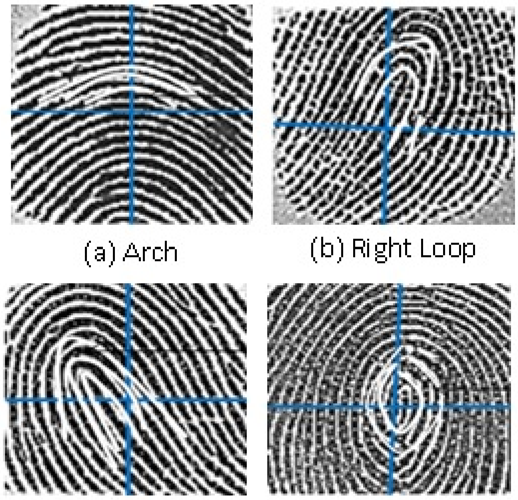


Fig. 2. Determined pattern types

pattern types for a reference (R) and a template (T) image leads to the non-match conclusion while same extraction of same pattern type leads to the next phase of the algorithm that is used to investigate if they are from same finger or not. The investigation is based on the pair setx, y, θ and $x^{\mid}$, $y^{\mid}$, $\theta^{\mid}$. x, y and θ are respectively the x-coordinate, y-coordinate and the orientation of the extracted singular point for the reference image while $x^{\mid}$, $y^{\mid}$, $\theta^{\mid}$ are respectively the x-coordinate, y-coordinate and the orientation of the extracted singular point for the template image. R and T are said to match if:

$$| x < x^{\mid} | \leq X_T \,\&\, | y < y^{\mid} | \leq Y_T \,\&\, | \theta < \theta^{\mid} | \leq \theta_T \tag{10}$$

4. Experimental Study

The experimental study of the proposed fingerprint individuality model was carried out in a Microsoft Windows 10 Professional platform on HP Pavilion Core i7 8.00GB RAM 750 GB HDD. Matrix Laboratory (Matlab) R2018a was used as frontend while Microsoft Access Relational Database Management System served the backend. Benchmarked FVC2002 fingerprint database served as experimental dataset. The database comprises of four datasets DB1, DB2, DB3 and DB4 and 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. Images in the four datasets were enrolled using low-cost capacitive fingerprint reader from multiple sources and of varied quality. A subset of the extracted singular point characteristics for dataset DB1 images is presented in Table 2.

TABLE 2
A subset of the extracted singular point characteristics

Image	Core	Delta	Y	X	Orient
101-1	1	0	233	171	0.2587
101-2	1	0	152	135	0.0123
101-3	1	0	175	111	0.5931
101-4	1	0	264	166	0.3257
101-5	1	0	237	185	0.4271
101-6	1	0	182	58	2.0832
101-7	1	0	192	269	0.1863
101-8	1	0	199	117	0.6193
102-1	1	0	116	194	0.5555
102-2	1	0	198	230	0.8705
102-3	1	0	203	209	0.2418
102-4	1	0	161	222	0.3603
102-5	1	0	118	218	0.4148
102-6	1	0	208	145	0.5389
	0	1	265	203	0.6742
102-7	1	0	200	196	0.3701
102-8	1	0	164	116	0.2847

Results from the experimental studies showed how the model successfully detects all categories of fingerprint pattern. The results for left loop with delta and whorl pattern type detections are shown in Figure 3.

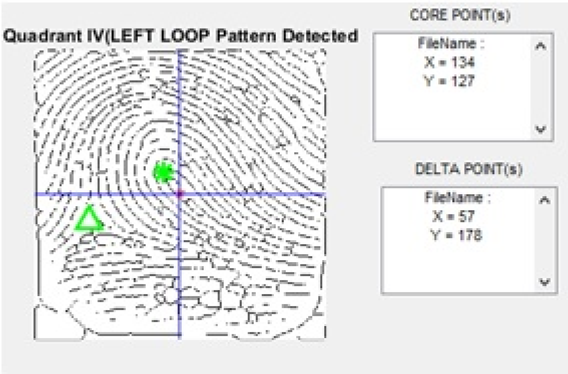
The extraction of the left loop pattern shown in Figure 3 (a) is based on the x-y coordinates of the point of optimal turning of the ridges. At this point, the x coordinate is below xo while the y coordinate is above yo. The delta point is extracted based on its Poincare index value which falls within the range 0.5 to -1 (see equations 1-3). As shown in Figure 3(b), the algorithm successfully extracted two points with optimal ridge turning for the whorl pattern. The two points though closely located around the origin, differ in the y coordinates (y1 = 166, y2 = 114) while the x coordinates are significantly close (x1 = 164, x2 = 168). Summarily, the left loop pattern is detected based on the location of its core point on the fourth quadrant while the whorl pattern is detected based on two core points that are located on the first and third quadrants and very close to the origin. Table 3 presents the 100-scale matrix of the matching scores for some fingerprint images (shown in Figure 4) selected from FVC2002 DB1 dataset. It is revealed that only the diagonal values are 100 while non-diagonal values are lesser. The diagonal values indicate correct matching of the corresponding images which are similar and from same finger while the non-diagonal values show the degree of match or similarity among the respective pair of images from different sources. The higher the value, the more the closeness of the feature attributes of the images.

Visual inspection of the images shown in Figure 4 confirms pattern type, orientation, dimension and quality variations and hence the justification for the acceptability of the different similarity values displayed in Table 3.

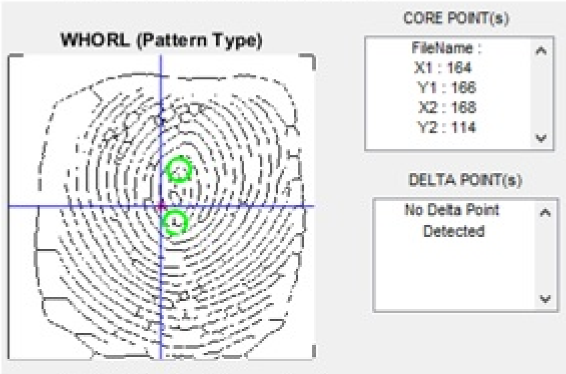
The error rates for the model were computed based on the False Non-Match Rate (FNMR) and the False Match Rate (FMR). The computation is premised on partitioning the 80 fingerprint images in each of the four datasets into eight (8) groups. Each group comprises of ten (10) fingerprints from same finger. FNMR was obtained based on matching of each fingerprint in every group with other nine from the same group while FMR was obtained based on matching of each of the eighty fingerprints with all the seventy fingerprints in other groups. Several matching thresholds were used for conducting the error rate experiments. When the threshold value was too high, it was observed that the system generated a very high FNMR and very low FMR. This implies that there is a possibility that fingerprint images from the same finger may not be matched under such threshold.

Similarly, when the value was too low, the system generated very low FNMR and very high FMR. This also implies that there is a very high possibility that fingerprint images from different fingers may be matched and taken as images from same finger under such threshold. The most experimentally proven and reliable values of FNMR and FMR were obtained by adopting the matching threshold of 95% presented in [24],[25]. Based on this threshold, the obtained FNMR and FMR for the four datasets in FVC2002 fingerprint database are shown in Table 4. The variation in the obtained FNMR and FMR results revealed significant differences in the quality of the images from the four datasets.

The very lower values obtained for the FMR in all cases imply correct identification of fingerprint images from same and different fingers. However, the obtained FNMR results established the



(b) Left loop pattern extraction



(a) Whorl pattern extraction

Fig. 3. Results of Fingerprint Pattern Type Detection

Fig. 4. Experimehtal images

degree of failure to matching of fingerprint from the same finger. Likely factors that could be responsible for this degree of failure include variation in pressure, rotation, translation and contact area during fingerprint enrolment. These factors constrained images from the same finger to show differences in quality, contrast and noise levels. The average matching times in seconds for FNMR and FMR for the four datasets are presented in Table 5. It is revealed that dataset DB3 has the lowest FNMR average matching time of 0.76 while dataset DB1 has the highest FNMR average matching time of 1.09. Similarly, dataset DB4 has the lowest FMR average matching time of 0.66 while dataset DB1 also recorded the highest average FMR matching time. The lowest FNMR average matching rate for dataset DB3 implies that the dataset is best in term of quality and consequently, experienced reduced enhancement and feature extraction computations.

TABLE 3
Results of Fingerprints Pattern Type Detection

Im	1_1	2_1	3_1	4_1	5_1	6_1	7_1	8_1	9_1	10_1
1_1	100	53.84	48.14	46.74	50.41	49.15	51.18	44.18	40.86	45.71
2_1	53.84	100	58.12	45.17	56.71	48.47	49.16	47.42	51.15	41.26
3_1	48.14	58.12	100	60.15	55.16	58.44	61.14	49.16	40.20	50.34
4_1	46.74	45.17	60.14	100	47.14	50.71	57.94	51.84	49.19	50.47
5_1	50.41	56.71	55.16	47.14	100	49.77	54.24	55.32	48.72	50.13
6_1	49.15	48.47	58.44	50.71	49.77	100	64.72	61.72	59.22	60.14
7_1	51.18	49.16	61.14	57.94	54.24	64.72	100	49.28	48.17	45.14
8_1	44.18	47.42.84	49.16	51.84	55.32	61.72	49.28	100	40.62	41.44
9_1	40.86	51.15	46.20	49.19	48.72	59.22	48.17	40.62	100	47.14
10_1	45.72	41.26	50.34	50.47	50.13	60.15	45.14	41.44	47.14	100

TABLE 4
FNMR and FMR values for FVC2002 datasets

Dataset	FNMR(%)	FMR(%)
DB1	1.55	0.0012
DB2	1.01	0.0014
DB3	1.50	0.0001
DB4	1.82	0.0001

TABLE 5
Average Matching Time in seconds for the four datasets

Dataset	FNMR	FMR
DB1	1.09	1.91
DB2	0.88	1.83
DB3	0.76	0.92
DB4	0.94	0.66

Table 6 summarizes the comparison of the average FNMR and FMR for the four datasets in FVC2002 fingerprint database for the current study and the works presented in [13],[24],[25]. The authors in [13] and [25] developed feature based models for fingerprint matching. While the authors in [14] used morphological operation along with AGNN classifier for the investigation of fingerprint individuality, the authors in [15],[19],[20],[21],[24] developed minutiae based model. Statistical approach was used to investigate the individuality of fingerprints in [26]. The similarity of the methods presented by these authors in the areas of the underlying techniques as well as their choice of FVC2002 fingerprint database for experimental studies informed their selection for the comparative analysis. The values reported for [13],[21],[24],[25],[26] in Table 6 were as stated by their respective authors while those reported for [14],[15],[19],[20] were experimentally determined in the course of this research using their respective algorithms. Table 6 reveals that the current study produced lowest FMR while it came behind the ones presented in [20],[24] on results for FNMR. This implies that the new model competed favorably and exhibited more robustness and efficiency.

5. Conclusion

Previous research works had emphasized minutiae or feature characteristics for the investigation of fingerprint individuality without much attention on singular point and pattern type. Fingerprint individuality models from previous works are noted for computational complexities, susceptibility to intra and inter class variations,

TABLE 6
Comparative Analysis

Dataset	FNMR(%)	FMR(%)
Ref. [13]	05.00	0.8000
Ref. [14]	01.42	0.0287
Ref. [15]	03.24	0.3029
Ref. [19]	03.27	0.1258
Ref. [20]	01.41	0.5465
Ref. [21]	01.99	0.2049
Ref. [24]	01.37	0.5000
Ref. [25]	03.44	0.2000
Ref. [26]	17.09	0.8400
Current Study	01.47	0.0007

exhibition of poor performances with noisy or degraded images, lack of consideration for local orientation as well as reliance on transformation. However, the proposed model advanced the existing works by focusing on singular point and pattern type characteristics as instruments for establishing individuality among fingerprints with less computation and improved accuracy. The proposed model successfully examined the various fingerprint pattern types and their attributes. For reference and template fingerprints with same pattern types, the characteristics of the extracted singular points from the two images formed the basis for the investigation on whether they are from same finger or not. Metrics such as average matching time, false non-match rate and false match rate formed the bases of establishing the viability and the functionality of the model.
Obtained results for these metrics were satisfactory and established the feasibility of the model for practical implementation of Automated Fingerprint Identification System (AFIS). It is important to state that the performance of the proposed model depends on the accurate enhancement of the fingerprint images which in turn depends on the quality of the image. For extremely poor quality fingerprint image, there is the likelihood of poor enhancement as well as extraction of false or multiple singular points which will ultimately lead to misleading pattern type and matching results.

6. Acknowledgments

The authors would like to thank the reviewers for their inputs in the form of review that led to the improvement of the review paper.

References

[1] G. B. Iwasokun, O. C. Akinyokun and C. O. Angaye, Fingerprint Matching using Neighbourhood Distinctiveness, International Journal of Advanced Computer Applications, Vol. 66, No. 21, pp.1-8, 2013.
[2] S. U. Maheswari, and E. Chandra, A Novel Fingerprint Recognition using Minutiae features, International Journal of Engineering Science and Technology, Vol. 5, No. 2, pp. 413-418, 2013.
[3] A. Tukur, Fingerprint Recognition and Matching using Matlab, International Journal of Engineering and Science, Vol. 4, Issue 12, ISSN: 2319-1805, pp.1-6, 2015.
[4] G. B. Iwasokun, Fingerprint Matching Using Minutiae-Singular Points Network, International Journal of Signal Processing, Image Processing and Pattern Recognition, Vol. 8, No. 2, pp. 375-388, 2015.
[5] J. Wang, Finger Image Quality Based on Singular Point Localization, MSc Thesis. Department of Informatics and Mathematical Modeling, Technical University, Denmark, 2013.
[6] S. C. Dass, C. Y. Lim and T. Maiti, A generalized mixed Model Framework for Assessing Fingerprint Individuality in Presence of Varying Image Quality, Annal of Applied Statistics, Vol. 8 No.3, pp. 1314-1340, 2014.
[7] K. Sondhi and Y. Bansal, Fingerprint Matching Using Minutiae Points, International Journal of Computer Science, Vol. 5, No.1, pp. 226-236, 2014.
[8] S. Pankanti, S. Prabhakar and A. K. Jain, On the individuality of Fingerprints, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 24, No. 8, pp. 1010-1025, 2002.
[9] Y. Zhu, S. Dass and A. K. Jain, Statistical Models for Assessing the Individuality of Fingerprints, IEEE Trans on Information Forensics and Security, Vol.2, pp.391-401, 2007.
[10] G. B. Iwasokun and O. C. Akinyokun,Singular-Minutiae Point relationship-based approach to fingerprint Matching, Artificial Intelligence Research, Vol.5, No.1, pp 78-86, 2016.

[11] N. Azad, A New Algorithm for Minutiae Extraction and matching in Fingerprint, PhD Thesis. Department of Electrical and Computer Engineering, Brunel University, 2012
[12] V. Akhil, Minutiae Local Structures for Fingerprint Indexing and Matching, MSc Thesis. Department of International institute of Information Technology, India, 2013.
[13] A. K. Jain, J. Feng and K. Nandakumar, Fingerprint Matching, IEEE Computer Society, pp. 36-44, 2010
[14] S. R. Borra, G. J. Reddy and E. S. Reddy, Classification of fingerprint images with the aid of morphological operation and AGNN classifier, Applied Computing and Informatics, 14, pp. 166–176, 2018
[15] S. Socheat and T. J. Wang, Fingerprint Enhancement, Minutiae Extraction and Matching Techniques. Journal of Computer and Communications, 8, pp. 55-74, 2020.
[16] J. Chen and Y. Moon, A Minutiae-Based Fingerprint Individuality Model, Proceedings of Computer Society International Conference on Computer Vision and Pattern Recognition, Minneapolis, Minnesota, USA, 18-23 June 2007.
[17] Y. Chen and A. K. Jain, Beyond Minutiae: A Fingerprint Individuality Model with Pattern, Ridge and Pore Features, Proceedings of International Conference on Biometric, pp.523-533, 2009.
[18] O. Ajala, M. Al-Jamea and C. Iliopoulos, Fast Fingerprint Recognition Using Circular String Pattern Matching Techniques, 2016. https://www.thinkmind.org/articles/patterns _2016_2_40_70041.pdf
[19] J. K. Appati, P. K. Nartey, E. O. and I. W. Denwar, Implementation of a Transform-Minutiae Fusion-Based Model for Fingerprint Recognition, International Journal of Mathematics and Mathematical Sciences, pp. 1-12, 2021.
[20] O. Loyola-González, E. F. Mehnert, A. Morales, J. Fierrez, M. A. Medina-Pérez and R. Monroy, Impact of Minutiae Errors in Latent Fingerprint Identification: Assessment and Prediction, Applied Sciences, 11, 2021.
[21] M. M. H. Ali, V. H. Mahale, P. Yannawar and A. T. Gaikwad, Fingerprint Recognition for Person Identification and Verification Based on Minutiae Matching, Proceedings of International Conference on Advanced Computing, February 2016.
[22] G. B. Iwasokun, O. C. Akinyokun, B. K. Alese and O. Olabode, Fingerprint Enhancement: Segmentation to Thinning, International Journal of Advanced Computer Science and Applications, Vol. 3 No. 1, pp.15-23, 2012.
[23] G. B. Iwasokun and O. C. Akinyokun, Fingerprint Singular Point Detection Based on Modified Poincare Index Method, International Journal of Signal Processing, Image Processing and Pattern Recognition, Vol. 7, No. 5, pp.259-272, 2014.
[24] M. Shahram and F. Ali, A Matching Algorithm of Minutiae for Real Time Fingerprint Identification System, World Academy of Science, Engineering and Technology, Vol.60, pp.595-599, 2009.
[25] G. B. Iwasokun, Development of a Hybrid Platform for Pattern Recognition and Matching of Thumbprints, PhD Thesis, Department of Computer Science, Federal University of Technology, Akure, 2012.
[26] Y. Zhu, S. Dass and A. K. Jain, Statistical Models for Assessing the Individuality of Fingerprints, IEEE Trans on Information Forensics and Security, Vol. 2, pp.391-401, 2007.