Experimental Study on the Effect of Pattern Variation and Feature Points on Fingerprint Matching

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Abstract---- **Fingerprint has been adjudged as the most reliable means of identification and authentication of an individual because of its uniqueness, high immutability and unchanging patterns. Typically, the ridges of fingers consist of different pattern types whose attributes are often extracted for matching during fingerprint classification. The occurrence of these patterns vary among fingerprint, which has significantly affected the accuracy of fingerprint recognition and classification processes. This paper therefore focuses on the investigation of the impact of pattern variation, singular points and feature points on fingerprint matching. The investigation was based on benchmarked FVC2000, FVC2002, FVC2004 and FVC2006 fingerprint databases which comprise four datasets each from different sources and of varied types. The obtained false non match rate (FNMR), false match rate (FMR), total matching time (TMT) and average matching time (AMT) values revealed that use of multiple matching criteria will lead to extension in the fingerprint matching time.**

Keywords---- fingerprint, pattern variation, singular point, features, matching.

I. INTRODUCTION

Fingerprint is an impression of skin which consist of ridges and valleys that is left or made by pressing an inked finger on the surface of paper or object. It is an imprints formed by the friction ridges of the skin and fingers. One of the motivating factors of using fingerprint is the uniqueness and permanence of its pattern and its public acceptance as a reliable evidence in a court of law. The uniqueness of a fingerprint is quantified by its pattern type as well as its features [1]. The ridges of finger form six major pattern types namely: arch, tented arc, left loops, right loop, twin loop and whorls, as shown in Figure 1 [1], [2].

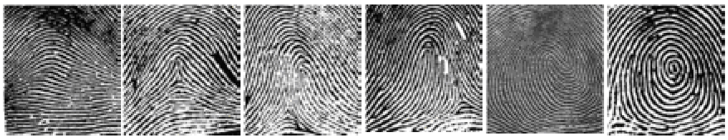


Figure 1: Types of fingerprint patterns

These patterns are ridges on the end of an individual's fingers that are arranged in a pattern of spirals and loops. They help humans to prevent slippery and sliding as well as to achieve firm grip and holding onto objects. Sir Francis Galton first introduced the technique for comparing fingerprints found at the crime scene with those of the suspect. Later, Sir Edward Henry developed the system of classifying fingerprints into three basic patterns, arches, loops and whorls. These were latter sub-divided into eight basic patterns which are used as benchmark database till today [3].

The arch is a type of ridges which make a rise round the core point and exit on the opposite side by making wave pattern at center. There are two type of arch pattern named plain arch and tented arch. Ridges enter one side and flow out or tend to flow out the other side with a rise of wave in the center in a plain arch. Whereas, in a tented arch, most of the ridges enter one side and flow out or tend to flow out the other side with a rise of wave in the center and the rest of the ridges form a definite angle. Less than 15% of all fingerprints are arches. [6 -7].

A loop is a type of fingerprint in which one or more of the ridges enter on either side, re-curve round, touch or pass the delta point to the core point and terminate or tend to terminate on or toward the same side from which such ridge or ridges entered. There are many types of loops such as left loop, right loop, double loop, left pocket loop and right pocket loop. Mostly, left and right loops are found in human fingerprint. In the left loop pattern, the ridges enter from the left side while they enter from the right side in the right loop pattern. About 50-60% of human fingerprints belong to this category [6]. Whorl Pattern is one of the basic patterns of the human fingerprint that have at least one ridge that tends to make a complete circuit. The ridges are usually circular round the core point. Types of whorl pattern are plain whorl, double loop whorl, central pocket loop whorl and accidental whorl. In plain whorl, one or more ridges form a complete revolution around the center with two deltas, while in double loop, two separate loops are present which sometimes surround each other. In central pocket loop, some ridges form a loop pattern which surrounds a central whorl and one delta while accidental loop consists of a combination of two different types of patterns with the exception of the plain arch, with two or more deltas. About 30% of human fingerprints belong to this category [7].

Fingerprint features can be classified into major and minor features that comprise of the following, ridge ending (terminator), bifurcation, lake or enclosure, short ridge or independent ridge, point or island crossover or bridge and spur [1]. Also, fingerprint features can be classified into level 1, level 2 and level 3. Level 1 features comprise those global patterns and morphological information. They are features that can be seen with naked eye. This include pattern type (arch, loop and whorl), ridge pattern, orientation, spatial frequency, curvature position and count, core and delta (singular points). These features do not contain sufficient information to uniquely identify fingerprint but are used for broad classification of fingerprint. Level 2 features or local features are the most prominent features called minutiae. There are about 150 different types of minutiae categorized based on their configuration. Among these minutiae types, ridge ending and ridge bifurcation are the most commonly used due to their ease of detection compared to other minutiae types. Level 3 features are the extremely fine intra ridge details present in fingerprint. Examples are sweat pores and ridge contours. The pore information (position, number and shape) is considered to be permanent, immutable and highly distinctive but not often used for matching since it requires high resolution of about 1000dpi to extract good quality fingerprint images [10].

Automated Fingerprint Identification System (AFIS) database is a global benchmarked fingerprint database where each dataset comprises of different fingerprint pattern in various qualities. This is possible due to factors such as, non-linear distortion, intra class variation, inter class similarity, among others which are associated with fingerprint processing and matching. The occurrence of these fingerprint patterns vary significantly in the database. The vast majority of fingerprint are represented by loop, which is highly abundant in all the fingers. In contrast, arch pattern type occur much less frequency. This paper therefore presents an investigation into the impact of pattern variation on fingerprint matching algorithm. Section 2 presents fingerprint matching while Section 3 presents fingerprint matching based on pattern variation. The experimental study based on fingerprint dataset jointly formulated by the Biometric Systems Laboratory, Bologna, Pattern Recognition and Image Processing Laboratory, Michigan and the Biometric Test Center, San Jose, United States of America is presented in Section 4. The conclusion drawn is presented in Section 5.

II. FINGERPRINT MATCHING

A number of fingerprint matching methods have been developed and prominent among them are minutiae-based matching, Feature-based matching and correlation based matching [6]. In minutiae-based matching, this method is widely adopted for the fact that fingerprint minutiae are generally known to be the most unique, durable and reliable features. During minutiae-based fingerprint pattern matching, the minutiae (mostly ridge ending and bifurcation) are extracted from gray-scale or thinned binary fingerprint images and store in extracted feature database. A fingerprint matching algorithm compares the correspondence pair of extracted minutiae and returns a degree of similarity by generating matching score. However, the quality of fingerprints affects the reliability of minutiae and therefore affects matching performance. The feature based pattern matching involves matching of a set of features of fingerprint with enrolled fingerprint in a database. The first step of the matching is to find available ridges in the fingerprint image for extraction process. The extracted ridges are normalized and classified according to their structure using store information. These normalized ridges undergo matching according to the extracted features. In correlation-based matching, the template and query fingerprint images are spatially correlated to estimate the degree of similarity between them. In general, the correlation is not a robust matching method due to presence of non-linear distortion that makes the global structure in impressions of the same finger very differently and the skin condition may significantly vary the image. Furthermore, 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. This method is helpful when minutiae information from fingerprint image is not able to extract [12]. Most of the Automated Fingerprint Identification System (AFIS) make use of fingerprint features such as minutiae (ridge ending and bifurcation) and singular points (core/delta). These features play very crucial roles and they are mostly used in fingerprint classification and matching techniques.

The authors in [8] developed a novel algorithm base on global comprehensive similarity with three steps to describe the Euclidean space-based relative features among minutiae. Firstly, the authors developed a minutiae-simplex that contains a pair of minutiae along with their associated textures, and its transformation-variant and invariant relative features employed for the comprehensive similarity measure and parameter estimated respectively. Secondly, the ridge-based nearest neighborhood among minutiae was used to represent the ridge-based relative features among minutiae. Lastly, the authors modeled the relationship between transformation and the similarity between two fingerprints in terms of histogram. The model developed is both effective and suitable for used in automated fingerprint identification system (AFIS). The authors in [9] presents fingerprint matching scheme that utilizes a ridge patterns to match fingerprint images. The algorithm used a set of 16 Gabor filters where spatial frequencies corresponds to the average inter-ridge spacing in fingerprint, and this is use to capture the ridge strength and equally spaced orientations. A ridge is then constructed using circular tessellation of filtered image which contain both global and local details in a fingerprint as a compact fixed length feature vector. Implementation of the matching was based on the Euclidean distance between two corresponding feature vector. Although, the algorithm tolerates small magnitudes of elastic distortion and local scaling due to finger pressure variation, it does not take care of significant nonlinear elastic distortion in the fingerprints.

III. FINGERPRINT MATCHING BASED ON PATTERN VARIATION

The proposed model for pattern variation-based fingerprint matching is divided into the pattern type phase and pattern type with feature phase as conceptualized in Figure 2. Each phase comprises of the pre-processing, feature extraction and matching. The image pre-processing phase is based on the algorithm proposed in [1,2,5].

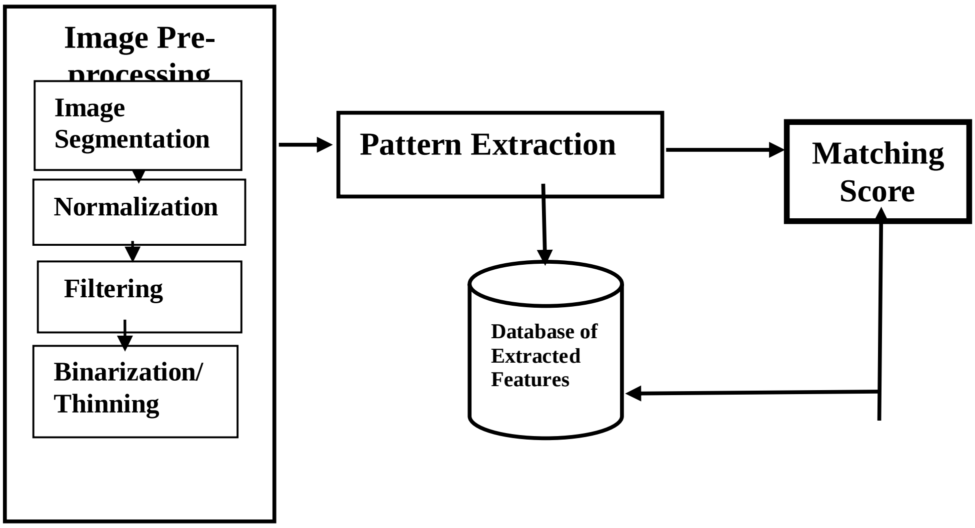


Figure 2: Conceptualization of the Proposed Model.

The determination of the fingerprint pattern type is based on the model proposed in [5]. It begins with splitting 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 first, second, third and fourth quadrants of the coordinate plane are computed based on Equations (1), (2), (3) and (4) respectively.

$$(1 < u < 0.5x)\ AND\ (0.5y < v < y) \tag{1}$$

$$(0.5x < u < x)\ AND\ (0.5y < v < y) \tag{2}$$

$$(0.5x < u < x)\ AND\ (1 < v < 0.5y) \tag{3}$$

$$(1 < u < 0.5x)\ AND\ (1 < v < 0.5y) \tag{4}$$

u and v are the coordinates of the core points, x and y are the row and column dimensions of the fingerprint image

The detection of the singular point characteristics in the second module begins with dividing the fingerprint image into blocks of size M x M. The computation of the orientation (directional flow) for the center pixel C(a, b) of each block is then carried out and followed by the determination of the singular points for a pixel (a, b) based on a modified Poincare index method presented as follow [1,2,5]:

$$I(a,b) = \pi^{-1} \sum_{s=1}^{2} \mu_s \tag{5}$$

$$\mu_s = \begin{cases} p(s) + \pi\ ;\ p(s) \leq -0.5\pi \\ p(s)\ ;\ p(s) > -0.5\pi \\ p(s) - \pi;\ \ otherwise \end{cases} \tag{6}$$

$$p(s) = |O_{s+1} - O_s|,\ O_{9=}O_1 \tag{7}$$

Where $I(a,b)$ represents singular point characteristics, (a,b) are orientation direction, μ_s is the computed point characteristic, $O_1, O_2, \ldots, O_8$ represents the orientation of the 3x3 neighbors of pixel (a, b). Based on these characteristics, the core point lies between -1 and -0.5 for $I(a, b)$ while the delta point is in the range 0.5 to -1.

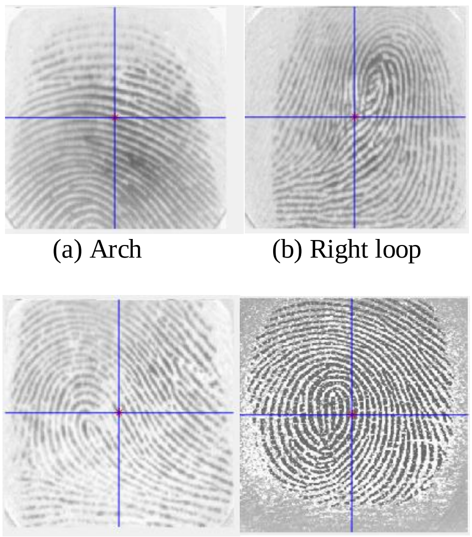
The arch, left loop, right loop and whorl pattern types are respectively determined based on the following steps [5]:

a. Given a core/delta point with coordinate point $P(\propto, \beta)$on a plane with origin $O(\propto_0, \beta_0)$, if $PO \leq \rho$, where ρ is the threshold, then an arch pattern is detected (see Figure 3(a)).

b. If $\propto < \propto_0$ and $\beta < \beta_0$, then the singular point is on first quadrant and a right loop is detected (see Figure 3(b))

c. If $\propto < \propto_0$ and $\beta > \beta_0$, then the singular point is on fourth quadrant and a left loop is detected (see Figure 3(c)).

d. If dual core points $(\propto_1, \beta_1)$ and $(\propto_2, \beta_2)$ are detected, then a whorl pattern is detected (see Figure 3(d)).



(a) Arch (b) Right loop

(c) Right loop (d) Whorl

Figure 3: Determined Pattern Types

The pattern matching is based on matching a reference (R) and a template (T) image which leads to process termination when pattern type differs while extraction of same pattern type leads to the next phase of the algorithm that is used to investigate if they are from the same finger or not. The matching is based on the pair set x^R, y^R, θ^R and x^T, y^T, θ^T. x^R, y^R and θ^R are respectively the x-coordinate, y-coordinate and the orientation of the extracted singular point for the reference image while x^T, y^T and $\theta^T$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:

$$|x^R < x^T| < X_T \ \& \ |y^R < y^T| < Y_T \ \& \ |\theta^R < \theta^T| < \theta_T \quad (8)$$

IV. EXPERIMENTAL STUDY

The experimental study of the proposed system 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 FVC2000, FVC2002, FVC2004 and FVC2006 fingerprint databases served as experimental dataset. Each of 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 qualities. A subset of the extracted pattern type and the combination of pattern type and singular point features for DB1 images are presented in Table 1a- 1b respectively**.**

Table 1a: A subset of the extracted pattern type characteristics

Image	Core	Delta	X	Y	Orientation	Pattern
1_1	1	0	168	205	0.2368	Left loop
1_2	1	0	164	152	0.2621	Tented arch
1_3	1	0	154	146	0.7523	Right loop
1_4	1	0	170	168	0.2097	Left loop
1_5	1	0	188	208	0.3101	Left loop
1_6	1	0	143	142	2.1574	Tented arch
1_7	1	0	196	184	0.1553	Right loop
1_8	1	0	147	190	0.0199	Right loop
2_1	1	0	133	126	0.2455	Left loop
2_2	1	0	218	108	0.6605	Right loop
2_3	1	0	109	201	0.1618	Tented arch
2_4	1	0	151	160	0.6803	Right loop
2_5	1	0	136	102	0.1488	Right loop
2.6	1 0	0 1	175 163	149 202	0.3229 0.8042	Whorl

2_7	1	0	176	100	0.1271	Left loop
2_8	1	0	126	144	0.1897	Left loop

Table 1b: A subset of the combination of the extracted pattern type and singular point features characteristics

Image	Core	Delta	X	Y	Orientation	Pattern
1_1	1	0	171	233	0.2587	Left loop
1_2	1	0	135	152	0.0123	Tented arch
1_3	1	0	111	175	0.5931	Right loop
1_4	1	0	166	264	0.3257	Left loop
1_5	1	0	185	237	0.4271	Left loop
1_6	1	0	58	182	2.0832	Tented arch
1_7	1	0	269	192	0.1863	Right loop
1_8	1	0	117	199	0.6193	Right loop
2_1	1	0	194	116	0.5555	Left loop
2_2	1	0	230	198	0.8705	Right loop
2_3	1	0	209	203	0.2418	Tented arch
2_4	1	0	222	161	0.3603	Right loop
2_5	1	0	218	118	0.4148	Right loop
2.6	1 0	0 1	145 203	208 265	0.5389 0.6742	Whorl
2_7	1	0	196	200	0.3701	Left loop
2_8	1	0	116	164	0.2847	Left loop

Results from the experimental studies showed how the algorithm successfully detected all categories of fingerprint patterns and features. The result of the extracted left loop with core/delta and whorl pattern type are shown in Figure 5 and Figure 6. Tables 2a-2b present the 100-scale matrix of the matching scores for the fingerprint images selected from FVC2000 DB1, FVC2002 DB1, FVC2004 DB1and FVC2006 DB1 respectively as shown in Figure 4.

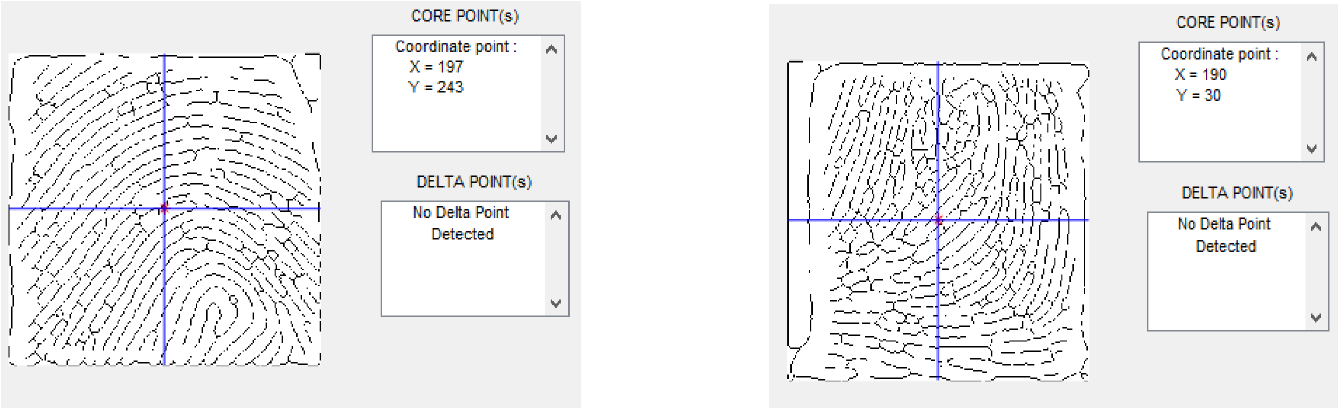
101_1 102_1 103_1 104_1
105_1

106_1 107_1 108_1 109_1
110_1

(a) Selected images from FVC2000 DB1

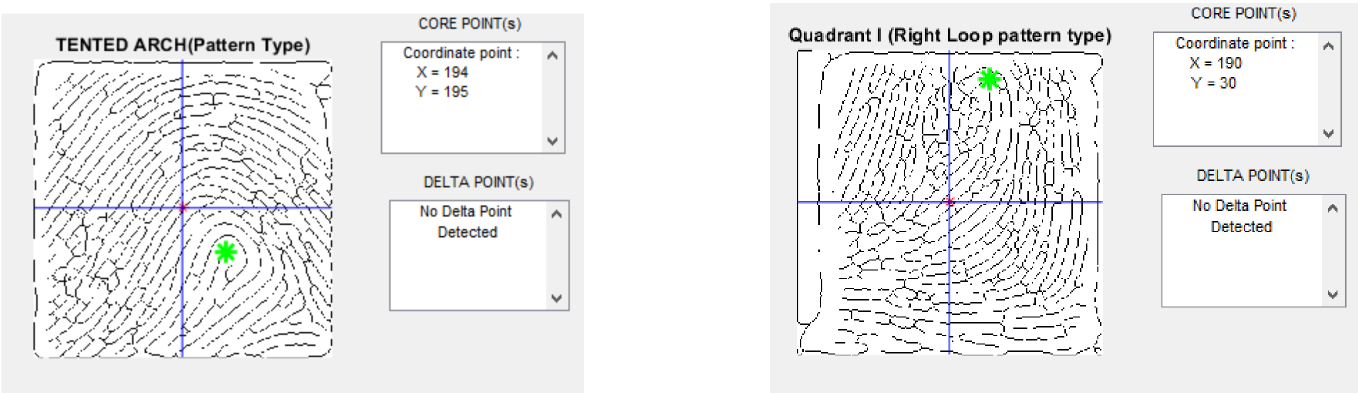
(b) Selected images from FVC2002 DB1

Figure 4: Samples of experimental images



(a) Tented arch pattern extraction (b) Right loop pattern extraction

Figure 5: Results of Fingerprint Pattern Type Detection



(a) Tented arch singular point extraction (b) Right loop singular point extraction

Figure 6: Results of Fingerprint Pattern Type with Singular Point Detection

The results for the tented arch and right loop with pattern type detections are shown in Figure 5, while the results for the tented arch and right loop with pattern type with core point detections are shown in Figure 6. The extraction of the tented arch pattern shown in Figure 6(a)is based on the x-y coordinates of the point of optimal turning of the extracted ridges. At this point, the x coordinate is above xo while the y coordinate is below yo. The core point is detected based on its Poincare index value which falls within the range -1 and -0.5 (see equations 5-7). In Figure 6(b), right loop pattern is detected when x coordinate is above xo while its correspondence y coordinate is also above yo. Summarily, a tented arch pattern is detected based on the location of core point on the second quadrant while a right loop pattern was extracted based on the core point at the first quadrant It is observed from the Tables 2a-2b that only the diagonal values are100 while non-diagonal values are lesser. The diagonal values indicate correct matching of the correspondence 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 closer a score is to 100, the greater the similarity of the images producing it and the greater the possibility they are from the same source. Similarly, scores closer to 0 indicates wide difference in the image and increased possibility they are from different source.

Table 2a- Results of Fingerprint Pattern Type Detection only

Im	1_1	2_1	3_1	4_1	5_1	6_1	7_1	8_1	9_1	10_1
1_1	100	60.14	55.16	58.44	61.14	49.16	46.20	50.34	49.87	37.52
2_1	60.14	100	48.90	47.14	42.98	50.12	41.89	39.12	40.56	42.45
3_1	55.16	48.90	100	60.01	56.16	58.67	60.34	49.19	41.20	49.34
4_1	58.44	47.14	60.01	100	50.56	49.87	51.90	50.56	47.41	56.13
5_1	61.14	42.98	56.16	50.56	100	50.01	46.89	51.91	45.78	51.55
6_1	49.16	50.12	58.67	49.87	50.01	100	55.56	58.45	53.78	52.78
7_1	46.20	41.89	60.34	51.90	46.89	55.56	100	61.98	59.56	60.51
8_1	50.34	39.12	49.19	50.56	51.91	58.45	61.98	100	45.76	48.78
9_1	49.87	40.56	41.20	47.41	45.78	53.78	59.56	45.76	100	50.76
10_1	37.52	42.45	49.34	56.13	51.55	52.78	60.51	48.78	50.76	100

Table 2b- Results of Fingerprint Pattern Type and singular point 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	73.81	68.18	66.74	50.41	69.15	61.18	54.18	49.06	55.77
2_1	73.81	100	68.19	75.14	56.71	68.47	59.77	57.44	51.99	41.88
3_1	68.18	68.19	100	70.19	58.17	78.40	65.14	59.14	60.20	58.39
4_1	66.74	75.14	70.19	100	67.17	58.72	57.92	67.84	79.44	65.47
5_1	50.41	56.71	58.17	67.17	100	69.27	55.44	65.39	68.70	70.03
6_1	69.15	68.47	78.40	58.72	69.27	100	64.77	61.92	69.28	60.77
7_1	61.18	59.77	65.14	57.92	55.44	64.77	100	69.18	68.97	65.08
8_1	54.18	57.44	59.14	67.84	65.39	61.92	69.18	100	60.67	71.74
9_1	49.06	51.99	60.20	79.44	68.70	69.28	68.97	60.67	100	67.18
10_1	55.77	41.88	58.39	65.47	70.03	60.77	65.08	71.74	67.18	100

The error rate for the model were computed based on the False Non-Match rate (FNMR) and the False Match Rate (FMR). The computation is based on partitioning the 80 fingerprint images in each of the four datasets into 8 groups. Each group comprises of 10 fingerprint 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 [11], [13]. Based on this threshold, the obtained FNMR and FMR for the four datasets in FVC2000, FVC2002, FVC2004 and FVC2006 fingerprint databases for pattern type matching only and pattern type with singular point feature are shown in Table 4 and Table 5 respectively. It was revealed from the results obtained that, the FNMR and FMR for matching of pattern type only are lesser in values compared to the values of FNMR and FMR for the combination of pattern type and singular point. 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 degree of failure to matching of fingerprint from the same finger.

Table 4: FNMR and FMR values for datasets for pattern types only

Datasets	FVC2000		FVC2002		FVC2004		FVC2006	
	FNMR (%)	FMR (%)	FNMR (%)	FMR (%)	FNMR (%)	FMR (%)	FNMR (%)	FMR (%)
DB1	1.01	0.0011	1.05	0.0012	1.52	0.0011	1.05	0.0012
DB2	1.02	0.0001	1.21	0.0011	1.07	0.0010	1.07	0.0014
DB3	1.04	0.0012	1.14	0.0002	1.50	0.0001	1.21	0.0001
DB4	1.41	0.0004	1.12	0.0011	1.25	0.0003	1.22	0.0004

Table 5: FNMR and FMR values for datasets for pattern types and singular point feature.

Datasets	FVC2000		FVC2002		FVC2004		FVC2006	
	FNMR(%)	FMR(%)	FNMR(%)	FMR(%)	FNMR(%)	FMR(%)	FNMR(%)	FMR(%)
DB1	1.42	0.0013	1.55	0.0012	1.50	0.0017	1.01	0.0015
DB2	1.02	0.0011	1.01	0.0014	1.07	0.0011	1.06	0.0014
DB3	1.57	0.0012	1.50	0.0001	1.52	0.0007	1.67	0.0008
DB4	1.49	0.0004	1.82	0.0001	1.74	0.0003	1.80	0.0004

Table 7: The total and average matching times in seconds for FNMR and FMR for the four datasets in each of the database for pattern type only

Datasets		FVC2000		FVC2002		FVC2004		FVC2006	
	TMT	FNMR	FMR	FNMR	FMR	FNMR	FMR	FNMR	FMR
DB1	1.24	0.04	0.12	0.04	0.11	0.06	0.32	0.04	0.51
DB2	1.11	0.06	0.20	0.05	0.15	0.02	0.30	0.01	0.32
DB3	1.08	0.06	0.14	0.03	0.14	0.04	0.27	0.04	0.36
DB4	0.85	0.03	0.19	0.03	0.17	0.03	0.33	0.03	0.40

Table 8: The total and average matching times in seconds for FNMR and FMR for the four datasets in each of the database pattern type and singular points.

Datasets		FVC2000		FVC2002		FVC2004		FVC2006	
	TMT	FNMR	FMR	FNMR	FMR	FNMR	FMR	FNMR	FMR
DB1	10.11	1.02	1.62	1.09	1.91	1.22	1.99	0.61	0.65
DB2	8.11	0.78	1.43	0.88	1.83	0.81	0.71	0.84	0.83
DB3	5,83	0.76	0.56	0.76	0.92	0.56	0.97	0.67	0.65
DB4	5.66	0.97	0.74	0.94	0.66	0.24	0.60	0.91	0.60

The total matching time and average matching times in seconds for FNMR and FMR for the four datasets for FVC2000, FVC2002, FVC2004 and FVC2006 are presented in Tables 7-8. It is revealed that all the datasets had lowest FNMR and FMR total and average matching time for the pattern type only. This is as a result of reduced speed of operational time, since the process will terminate when the pattern type differs, while the pattern type with feature recorded an increase in FNMR and FMR total and average matching time due to a longer time to extract and matching the pattern type and the singular point attributes. Also, an increase in matching time is due to the increase in pre-processing and extraction computations in this phase.

V. CONCLUSION

The impact of variation of fingerprint pattern has been critically examined. The algorithm implemented focused on the extraction of various pattern types and singular point features as instruments for the establishing the variability among fingerprints. The algorithm successfully examined the various fingerprint patterns and other features. Metrics such as false non match rate, false match rate, total matching time and average matching time are examined and form the basis of establishing the variability of the fingerprint. The average matching time is relatively high in the pattern type with feature phase than with the pattern type only. It is therefore implied that use of multiple matching criteria will lead to extension in the fingerprint matching time.

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