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A Fingerprint Pattern Classification Approach Based on the Coordinate Geometry of Singularities

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***Abstract*—The problem of Automatic Fingerprint Pattern Classification (AFPC) has been studied by many fingerprint biometric practitioners. It is an important concept because, in instances where a relatively large database is being queried for the purposes of fingerprint matching, it serves to reduce the duration of the query. The fingerprint classes discussed in this document are the Central Twins (CT), Tented Arch (TA), Left Loop (LL), Right Loop (RL) and the Plain Arch (PA). The classification rules employed in this problem involve the use of the coordinate geometry of the detected singular points. Using a confusion matrix to evaluate the performance of the fingerprint classifier, a classification accuracy of 83.5% is obtained on the five-class problem. This performance evaluation is done by making use of fingerprint images from one of the databases of the year 2002 version of the Fingerprint Verification Competition (FVC2002).**

***Index Terms*—Biometrics, Fingerprint, Core, Delta, Class.**

I. Introduction

Biometrics is an applied science that deals with the recognition of individuals using their uniqueness, which can occur in the form of their behavior and/or their physiological characteristics. This therefore implies that fingerprint biometrics is an applied science that deals with the recognition of individuals using the unique nature of their fingerprint patterns. Fingerprint biometrics is already playing an important role in the securing of information: personal, confidential and sensitive. This can largely be attributed to two main factors; one technical and the other one not so technical.

The technical factor is that fingerprint biometric systems are highly accurate when measured against systems that make use of other biometrics. A few examples of these other biometrics include speech, iris, hand geometry and palm veins. The non-technical factor is that fingerprint biometric systems carry a positive public perception, that is, they are generally accepted by the consumers. This is because consumers find these systems easy to use and less invasive.

A fingerprint recognition system is useful in both verification and identification transactions. A verification transaction is characterized by an instance where a user claims to be an authorized or known person by presenting some unique identifier to the system. This then causes the system to get the stored biometric associated with this identifier and prompts the user to present their biometric for comparison. This implies that the fingerprint recognition system verifies a user's claim by executing a 1-to-1 comparison.

An identification transaction is characterized by an instance where a user presents their biometric to the fingerprint recognition system, for the system to compare against the stored biometric entries until it finds a match. A worst case scenario is when the matching entry is located at the end of the database. For a database with N entries, the system is said to be executing a 1-to-N comparison. For a relatively large value of N, the performance of the fingerprint recognition system is negatively affected due to the prolonged duration of the query.

A prolonged query is indicative of the fact that the fingerprint recognition system requires a module that can serve to divide the database into smaller partitions, just before the query is executed. The concept of Automatic Fingerprint Pattern Classification (AFPC) is exactly what the fingerprint recognition system needs in order to effect the required database partitioning. The primary objective of this study is to develop and implement an automatic fingerprint pattern classifier, hereinafter referred to as a fingerprint classifier, that is both accurate and robust against the variations in fingerprint quality.

A relatively large number of partitions tends to improve the speed of the system because it reduces the search space significantly. However, this large number of partitions tends to reduce the accuracy of the classifier. This implies that one of the challenges is for the AFPC practitioner to deal with the trade-off between the number of required partitions, that is, the query duration and the required classification accuracy. This document focuses on the development of a fingerprint classifier, with its feasibility demonstrated on a five-class fingerprint problem. These chosen classes are the Central Twins (CT), Tented Arch (TA), Left Loop (LL), Right Loop (RL) and the Plain Arch (PA), and they are further explained in section IV of this document.

II. Fingerprint Features

Fingerprint features are those attributes of a fingerprint that may be useful either to classify or to uniquely identify the fingerprint. There are two main types of features, namely, the local features and the global features. Figure 1 shows the local features denoted by the two squares; and the global features denoted by the circle and the triangle.

A. Global Features

The fingerprint global features are identified by means of the local orientation of the fingerprint ridges, that is, the Orientation Field Curves (OFCs). These features occur in the form of a Core and/or a Delta, and they are normally located

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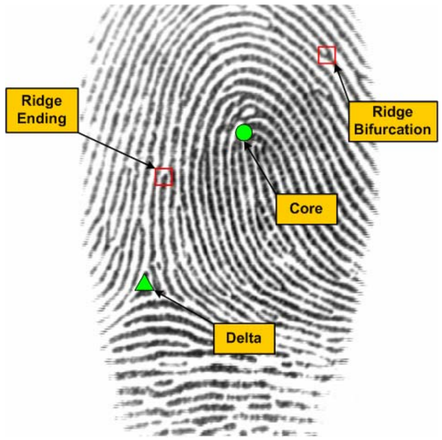


Fig. 1. The Local and the Global Features

in the central region of the fingerprint [1]. These features are referred to as the singular points of a fingerprint, or simply as the Singularities. A Core is the area around the center of the fingerprint loop and a Delta is the area where the fingerprint ridges tend to triangulate. Due to their sketchy nature, it can be concluded that both the Core and the Delta have a useful purpose in a fingerprint classification problem, where computational cost is a concern. This is because of the fact that a fingerprint classification practitioner can make use of these attributes to classify a fingerprint, while ignoring the minute details of the said fingerprint in order to realize computational efficiency.

B. Local Features

The fingerprint local features are those attributes that give the minute details about the fingerprint pattern. These features are known as the minutiae and they include ridge endings, ridge bifurcations and, although not very common, the islands [1]. These minutiae are what constitutes the uniqueness of every human fingerprint pattern. Due to their detailed nature, it is apparent that the local features have an important role to play in a fingerprint matching problem. This is because the key objective of the matching problem is to uniquely identify each fingerprint.

C. FingerCode Features

In addition to the fingerprint global and local features, there is a novel approach of representing fingerprint features, known as a FingerCode, that was introduced by Jain *et al* [2] for the purposes of fingerprint matching. It employs a bank of Gabor Filters to extract both the global and the local fingerprint features and represent them as a fixed length feature vector. In addition to being useful in the fingerprint matching problem, this approach has also been useful in the fingerprint classification problem [1].

III. Fingerprint Classification Approaches

This part of the document presents the theoretical foundation of the four main AFPC approaches, as used by various practitioners. These are: the modeling approach, the frequency domain approach, the syntactic approach and the structural approach.

A. Modeling Approach

This approach employs a model to automatically order a fingerprint pattern into the most probable class when presented with some features of that fingerprint. A good example of a model-based fingerprint classifier is an expert system that, when presented with the (x, y) position of the Core and/or the Delta of a fingerprint, extrapolates the most probable class that the fingerprint belongs to. This extrapolation is executed on the basis of the previous knowledge that the system has gained on different fingerprint patterns. A typical arrangement of a model-based classification system is depicted in figure 2.

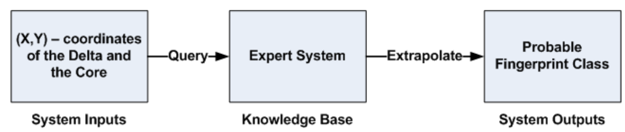


Fig. 2. A Typical Arrangement of a Model-Based Classifier

The model-based fingerprint classification approach is one of the most widely used methods by fingerprint classification practitioners. It mainly involves the use of computational intelligence techniques such as Artificial Neural Networks [3] and Support Vector Machines [4]. An example of an application that made use of these two techniques is the work done by Yao *et al* [5] in 2003. The main problem associated with a model-based approach is that, more often than not, fingerprint images are missing some of the features that should ideally serve as inputs to the model. This normally occurs during the impression of the fingerprint, where an enrollment participant impresses the fingertip in such a way that the fingerprint Delta is not captured as part of the image.

This non-existence of the point of Delta was observed many times during the course of this study, and Maltoni *et al* [6] agree with this fact, especially with regard to slapped fingerprints. This therefore implies that a practitioner that chooses the model-based approach is left with two options. The first option is to, during model optimization, remove the fingerprint images that are missing the Delta and remain with images that have the complete information. This, however, is too ideal for an application-driven study. The second option is to impute the missing information, creating another stand-alone project; Missing Data Imputation [7]. This does not simplify, but rather worsens the problem.

B. Frequency Domain Approach

Frequency domain approaches use some transformation such as the Fourier Transform [8] to get the frequency spectrum of the fingerprint and use it for classification. Examples of studies that employ this approach for fingerprint classification include the work of Fitz and Green [9]. A typical frequency domain scheme is depicted in figure 3, where the properties of the frequency spectrum are used to classify the fingerprint.

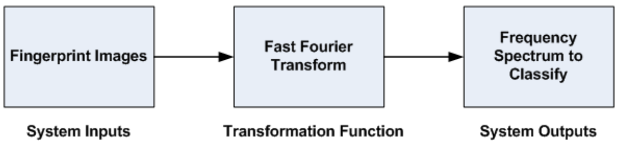


Fig. 3. Frequency Domain Approach Scheme

Because the transformation function usually requires an analog waveform as its input, frequency domain approaches rely on relatively complicated data extraction techniques. For example, Fitz and Green had to use a video camera to extract their data. The video camera's output was an analog waveform representing the fingerprint, which was then fed into the transformation function.

C. Syntactic Approach

This approach uses formal grammar to represent and classify fingerprints. This is a relatively old approach but it has not been receiving a lot of attention from practitioners. Studies that employ this approach for fingerprint classification include the work of Rao and Black [10].

D. Structural Approach

This method employs the flow direction of the fingerprint ridges, that is, the OFCs, to estimate the class that a fingerprint belongs to. These OFCs make up what is regarded as the orientation image ($\mathcal{O}$-image) of the fingerprint. Figure 4 shows an original fingerprint image together with its $\mathcal{O}$-image. This $\mathcal{O}$-image plays a useful role in identifying the positions of the singular points, as earlier pointed out in subsection II-A.

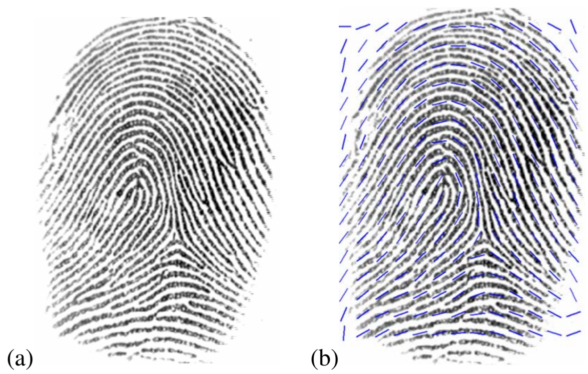


Fig. 4. Fingerprint Image (a) without OFCs and (b) with OFCs

A number of practitioners have successfully used this approach for fingerprint classification. Examples of these include Karu & Jain [11], Cappelli *et al* [12], Cappelli *et al* [13], Wang *et al* [14] and Zhang & Yan [15]. These practitioners took one of two approaches; use the $\mathcal{O}$-image to detect the singularities, then use the positions of these singularities to classify the fingerprint, or divide the $\mathcal{O}$-image into partitions that are in-turn used to classify the fingerprint. The former approach was used by [11], [14] and [15], while the latter was used by [12] and [13]. The classifier reported in this document uses the former approach, however, it has a number of competitive advantages when compared to the work of [11], [14] and [15]. These advantages are exposed by the subsequent sections of this document.

IV. Proposed Fingerprint Classes

This part of the document serves to explain the properties of the five fingerprint classes proposed in this study. It is worth mentioning that the most interesting classes are the TA, LL and RL.

A. Central Twins (CT) Class

The CT fingerprint class is characterized by fingerprints whose ridges have a circular pattern in the central part of the print. This fingerprint class accommodates two fingerprint patterns, one known as a Whorl and the other one known as a Twin Loop. One option is to combine these two patterns into one class, while another option is to separate these two patterns into their respective classes. In most instances, it is up to the practitioner to make the decision. In this study, these two fingerprint patterns are combined into one class, the CT class. This is because there is no major difference in the properties of the two patterns and they usually form a small fraction of most fingerprint databases. Figure 5 shows the two patterns that belong to the CT fingerprint class.

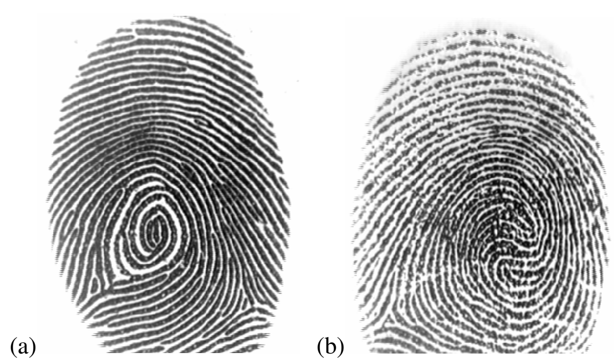


Fig. 5. CT Class Fingerprints: (a) Whorl and (b) Twin Loop

The two patterns have one thing in common. If the singular point detection module is well-designed, two Cores should be detected in the central area of each print. That is the reason why, in this study, they are referred to as fingerprints that belong to the CT class. They have two Cores, that look like twins, somewhere close to the center of the print. Under ideal circumstances, these fingerprints should each have two Cores and two Deltas. Most classification studies have used that as a classification rule, however this study also caters for fingerprints that have one or both Deltas missing.

This classification rule is formulated in section V-B of this document.

B. Tented Arch (TA) and Plain Arch (PA) Classes

The TA fingerprint class is characterized by fingerprints that have ridges entering the fingertip on one side, making a rise in the middle and leaving the fingertip on the other side. Figure 6 (a) depicts a fingerprint with a TA pattern. Under ideal circumstances, a TA fingerprint should have both a Core and a Delta, and this forms the basis of the classification rule in section V-C of this document.

(a) (b)

Fig. 6. The Arches: (a) Tented Arch (TA) and (b) Plain Arch (PA)

The PA fingerprint class is characterized by fingerprints whose ridges enter the fingertip on one side and leave on the other side. While these ridges do make a rise in the middle, this rise is not as sharp as the one in the TA fingerprints. Because of this less-sharp rise, the PA fingerprint has neither Core nor Delta, and this forms the basis of the classification rule presented in section V-F. Figure 6 (b) depicts a PA fingerprint.

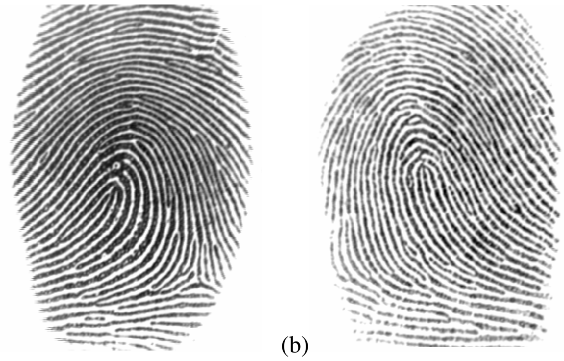
C. Left Loop (LL) and Right Loop (RL) Classes

The LL fingerprint class is characterized by fingerprints that have ridges entering the left side of the fingertip, forming a loop in the middle, and leaving the fingertip on the same, left, side. The RL fingerprints have the same characteristics except for the fact that the ridges enter and leave the right side of the fingertip. A LL fingerprint pattern is shown in Figure 7 (a), while Figure 7 (b) depicts the RL fingerprint. The fingerprints in both classes should, ideally, have a Core and a Delta in the central part of the print.

The presence of both the Core and the Delta is what many fingerprint classification practitioners have solely used to formulate their classification rules for these classes. However due to the way in which most enrollment participants impress their fingerprints, the Delta is usually not captured. This study presents a classification rule that also caters for fingerprints whose Deltas are not captured. This rule is presented in section V-E of this document.

V. Classifier Development

This part of the document presents the fingerprint classification rules that led to the successful implementation of the reported fingerprint classifier. Before the presentation of the



(a) (b)

Fig. 7. The Loops: (a) Left Loop (LL) and (b) Right Loop (RL)

classification rules, it is essential to become familiar with some of the terms adopted during the course of this study. These terms are defined in the following subsection.

A. Useful Terminology

1) Dynamic Plane: This is a Cartesian plane drawn across the ridge area of the fingerprint image. It moves along with the fingerprint ridge area regardless of where the participant places the finger on the capturing device. It is governed by an algorithm that dynamically computes the center of the fingerprint image foreground.

2) Pedestrian: This term is used to describe the lowered center of the fingerprint foreground, that is, the center at the foot of the fingerprint ridge area.

3) Auxiliary: The Auxiliary (AUX) is the angle that the base of the fingerprint image makes with the line joining the Core and the Pedestrian.

4) Conjugate Slope: The Conjugate Slope (C-Slope) is the gradient of the line joining the Core and the Delta. It is the conjugate of the conventional gradient, $M = \frac{\triangle y}{\triangle x}$. This is because, unlike a conventional plane where y-values increase upwards from the origin (center), the y-values in an image frame increase downwards from the origin (top-left corner).

B. Dual-Core Fingerprint Rule (DCFR)

***DCFR Proposition**: If two Cores are detected within a fingerprint image, then the fingerprint belongs to the CT class.*

The DCFR essentially proposes that, in order for a fingerprint to be classified as CT, the minimum requirement is that it should have two Core points. In addition to that, the fingerprint might have a single Delta, two Deltas or no Delta at all.

This means that a fingerprint whose Delta(s) went missing during impression, can still be correctly classified. This is the strength of the DCFR when measured against other techniques that have been used in the past. Karu and Jain [11] used a rule almost similar to the DCFR, however their rule required that, for a fingerprint to be ordered into this particular class, it should have two Cores and two Deltas, which is an ideal circumstance. Under practical conditions where many participants fail to have their Deltas captured, Karu and Jain's method will fail.

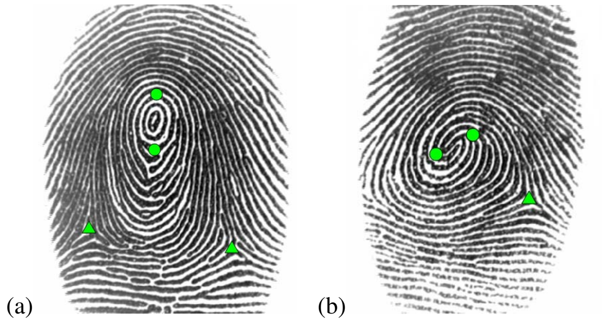


Fig. 8. DCFR: (a) Ideal Fingerprint and (b) Missing the Left Delta

Figure 8 (a) shows an ideal fingerprint having all the singular points, while figure 8 (b) shows a fingerprint that missed the left Delta during impression. Figure 9 (a) depicts a fingerprint that missed the right Delta during impression and a fingerprint that missed both Deltas is depicted in figure 9 (b).

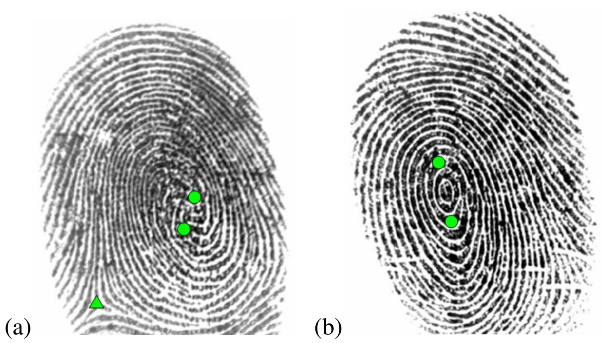


Fig. 9. DCFR: (a) Missing the Right Delta and (b) Missing both Deltas

C. Core-Delta Fingerprint Rule A (CDFR-A)

CDFR-A Proposition*: If a Core-Delta segment is detected within a fingerprint image, and the difference between the x-coordinates of the Core and the Delta (x-Diff) is less than or equal to* 30 *pixels, then the fingerprint belongs to the TA class.*

This rule essentially separates the TA fingerprint from the ideal LL or RL images. This is because of the fact that, under ideal circumstances, LL and RL fingerprints have a Core-Delta segment. Figure 10 shows an example of an image that has a Core-Delta segment, with x-Diff = 23 pixels.

D. Core-Delta Fingerprint Rule B (CDFR-B)

CDFR-B Proposition*: If a fingerprint image has a Core-Delta segment with x-Diff greater than* 30 *pixels, then the fingerprint belongs either to the LL or the RL class. If the C-Slope of the line joining the Core and the Delta is negative, then the fingerprint belongs to the LL class; else if the C-Slope is positive, the fingerprint belongs to the RL class.*

This rule separates the fingerprints belonging to the LL class from the ones belonging to the RL class. It is apparent that, for

Fig. 10. CDFR-A: x-Diff Less than or Equal to 30 Pixels

this rule to be applicable, both the Core and the Delta should be captured as part of the fingerprint image. Figure 11 (a) depicts a LL fingerprint with the line joining the Core and the Delta having a negative C-Slope. The RL fingerprint is depicted in figure 11 (b), with the line joining the Core and the Delta having a positive C-Slope.

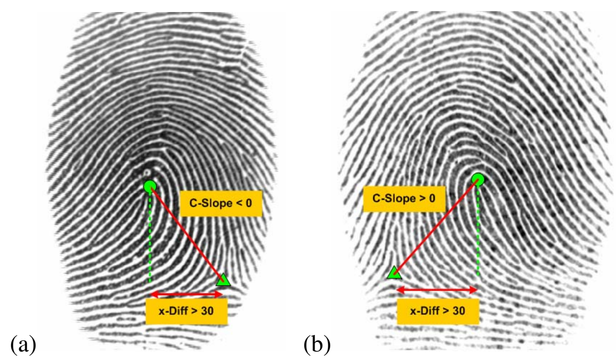


Fig. 11. CDFR-B: (a) LL Fingerprint with C-Slope <0 and (b) RL Fingerprint with C-Slope >0

E. Single-Core Fingerprint Rule (SCFR)

SCFR Proposition*: If a fingerprint image has a single Core and the AUX is acute, then the fingerprint belongs to the LL class; but if the AUX is obtuse, the fingerprint belongs to the RL class.*

This rule plays an important role in the process of classifying fingerprint images with incomplete information. Most fingerprint classifiers that rely on the geometry of singularities [11], [15] normally reject such images and ask for a resend. However it is not in the best interest of the fingerprint classification practitioner to do so. This is because of the fact that, under ideal circumstances, most enrollment participants slap their fingers in such a way that the Deltas are not captured by the fingerprint reader. This therefore implies that, for an application-driven study, it is in the best interest of the practitioner to either estimate the missing information or make a decision in the absence of the said information.

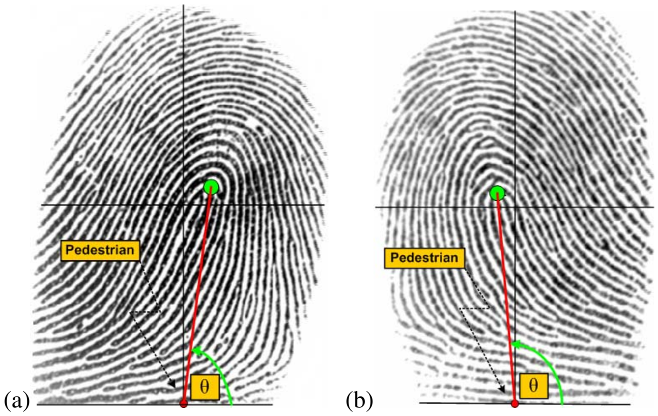


Fig. 12. SCFR: (a) LL Fingerprint with Acute AUX and (b) RL Fingerprint with Obtuse AUX

Figure 12 (a) depicts a LL fingerprint missing a Delta, with the AUX (denoted as θ) less than 90 degrees, while figure 12 (b) shows a RL fingerprint with the AUX greater than 90 degrees. The simplified version of the SCFR is that all the LL fingerprint images missing a Delta have a Core that lies in either the first or the fourth quadrant of the dynamic plane. For the RL images missing a Delta, the Core lies either in the second or the third quadrant of the dynamic plane.

F. Absent-Core Fingerprint Rule (ACFR)

***ACFR Proposition**: If a fingerprint image has neither Core nor Delta, then the fingerprint belongs to the PA class.*

This is probably the least interesting rule, and it has been used by many fingerprint classification practitioners, without stating it in a formal manner. A fingerprint image that subscribes to this rule is depicted in figure 6 (b).

VI. System Overview

Following the outline of the classification rules in the previous section, a block diagram showing the inter-relationship of the proposed classification rules can be presented. The said diagram is depicted in figure 13. The first block contains two processes; fingerprint image capturing and the pre-processing of the image. The image is pre-processed in order to eventually extract the global features that are useful to the classification module. These pre-processes include contrast enhancement, ridge segmentation, orientation image computation, orientation image smoothing and singular point detection.

VII. Classifier Performance Evaluation

In order to evaluate the performance of the proposed classifier, Database 1_a of the 2002 version of the Fingerprint Verification Competition (FVC2002) is used as the test data. A set of two measures is used to evaluate the performance of the reported fingerprint classifier. These are; the Classification Accuracy and the Accept-Reject Rates.

A. Classification Accuracy

The fingerprint images are classified by a fingerprint classification expert before running a total (TOT) of 431 data instances through the proposed classifier. The results obtained from this evaluation are recorded in table I.

TABLE I
FIVE-CLASS EXPERIMENTAL RESULTS TESTED ON FVC2002 DB1_A

Actual			As				
	CT	LL	PA	RL	TA	UKN	TOT
CT	**83**	05	00	04	00	01	93
LL	00	**108**	02	15	00	00	125
PA	00	00	**15**	01	00	00	16
RL	02	20	01	**96**	03	00	122
TA	01	05	04	07	**58**	00	75
			83.5%				431

Looking at table I, it can be observed that a total of 360 fingerprints are correctly classified, 70 are mis-classified and only 1 is classified as unknown (UKN). The results in table I give a classification accuracy of 83.5%, where this accuracy is defined by:

$$Accuracy = \frac{M}{T} \times 100, \tag{1}$$

where M is the sum of the main diagonal of the confusion matrix and T is the number of data instances in the test sample.

TABLE II
FOUR-CLASS EXPERIMENTAL RESULTS TESTED ON FVC2002 DB1_A

Actual		As				
	A	CT	LL	RL	UKN	TOT
A	**77**	01	05	08	00	91
CT	00	**83**	05	04	01	93
LL	02	00	**108**	15	00	125
RL	04	02	20	**96**	00	122
			84.5%			431

Because of the similarities in the OFCs of the PA and TA images, many fingerprint classifiers find it difficult to distinguish PA fingerprints from the TA fingerprints. This limitation is one of the reasons why some practitioners choose not to use structural fingerprint classifiers. As a result of that limitation, many fingerprint classification practitioners, like Karu and Jain [11], combine the PA and the TA fingerprints into one Arch (A) class. This is done in order to improve the accuracy of the fingerprint classifier. As an example, Karu and Jain reduced a 5-class problem to a 4-class problem, and the accuracy of their classifier moved from 85.4% to 91.4%.

The classifier reported in this document, however shows a certain level of immunity against that PA-TA confusion. This is, firstly, confirmed by the classification accuracy obtained from the test results in table II, where there is only 1%

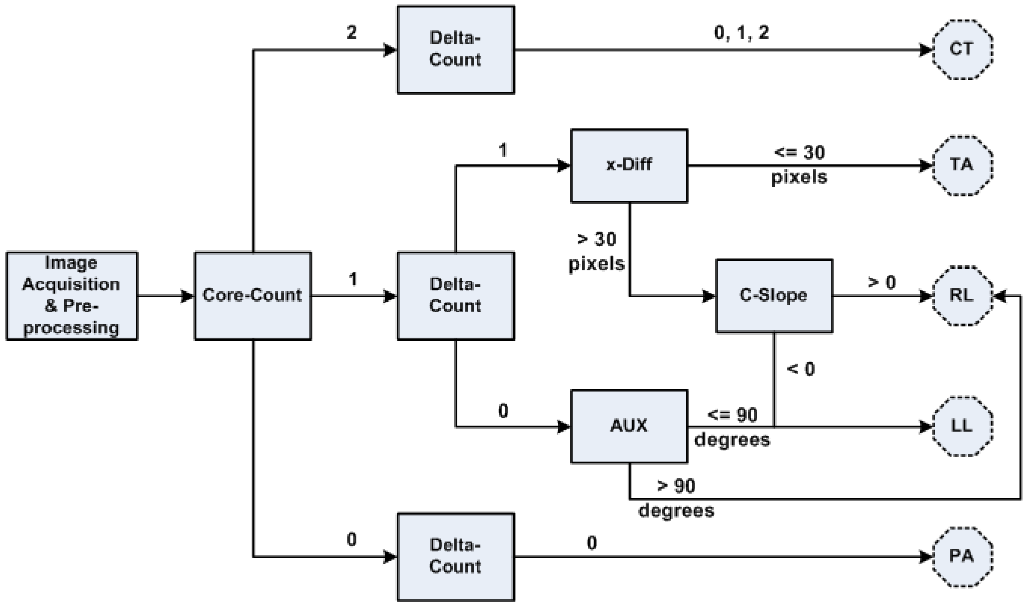


Fig. 13. Fingerprint Classification System Block Diagram

improvement in the accuracy, as the number of classes is reduced. This immunity is also confirmed by just looking at the PA and TA results in table I. It can be observed that not even a single PA fingerprint is mis-classified as TA and, out of 75, only 04 TA fingerprints are mis-classified as PA.

B. Accept-Reject Rates

Following the classification accuracy measured in the previous section, a total of 4 Accept-Reject rates is defined in order to further evaluate the performance of the reported fingerprint classifier. These are: the True Accept Rate (TAR), the True Reject Rate (TRR), the False Accept Rate (FAR) and the False Reject Rate (FRR). The results obtained from this evaluation are summarized in table III and the definitions for the different rates are provided in the following subsections.

TABLE III
REJECT AND ACCEPT RATES

	TAR	TRR	FAR	FRR
CT	89.2%	99.1%	0.9%	10.8%
LL	86.4%	90.2%	9.8%	13.6%
PA	93.8%	98.3%	1.7%	6.2%
RL	78.7%	91.3%	8.7%	21.3%
TA	77.3%	99.2%	0.8%	22.7%
AVE	85.08%	95.62%	4.38%	14.92%

1) True Accept Rate (TAR): This is a measure of the fingerprints that are rightfully accepted as part of a certain fingerprint class. An example of an event that increases the TAR of the TA class is a TA fingerprint (as manually classified by a fingerprint expert) being classified as a TA fingerprint (as classified by the automatic fingerprint classifier). The TAR of a particular fingerprint class is mathematically modeled as:

$$TAR_{class} = \frac{C}{S} \times 100, \tag{2}$$

where C is the number of fingerprints that are correctly accepted and S is the total number of fingerprints in that particular class. For a good fingerprint classifier, the average (AVE) TAR value should approach 100%. Any value greater than 80% should be sufficient.

2) True Reject Rate (TRR): This is the measure of the fingerprints that are correctly excluded from a certain fingerprint class. An example of an event that increases the TRR of a CT class is a non-CT, for instance LL, fingerprint being rejected by the CT class. The TRR of a particular fingerprint class is mathematically modeled as:

$$TRR_{class} = \frac{TOT - S - F}{TOT - S} \times 100, \tag{3}$$

where F is the total number of fingerprints that are wrongfully rejected, and the other symbols have the same meaning as before. Similarly, for a good fingerprint classifier, the average (AVE) TRR value should approach 100%.

3) False Accept Rate (FAR): This is the measure of the fingerprints that are accepted by a certain fingerprint class, while not belonging to that particular class. An example of an event that increases the FAR of a CT class is a non-CT, for instance LL, fingerprint being classified as a CT fingerprint. The FAR of a particular fingerprint class is mathematically modeled as:

$$FAR_{class} = \frac{F}{TOT - S} \times 100, \tag{4}$$

where all the symbols have the same meaning as before. For a good fingerprint classifier, the average (AVE) FAR value should approach 0%. Any value less than 20% should be sufficient.

4) False Reject Rate (FRR): This is a measure of the fingerprints that are rejected by a certain fingerprint class, while they belong to that class. An example of an event that increases the FRR of a LL class is a LL fingerprint being classified as non-LL, for instance RL. The FRR of a particular fingerprint class is mathematically modeled as:

$$FRR_{class} = \frac{K}{S} \times 100, \tag{5}$$

where K is the number of fingerprints that are wrongfully accepted and S has the same meaning as before. Similarly, for a good fingerprint classifier, the overall FRR should approach 0%.

VIII. Discussions and Conclusions

This document presented and discussed the rules proposed and subsequently employed in the development and implementation of a structural fingerprint classifier. The key fingerprint features used in this classification problem are the Core and the Delta, with a total of five fingerprint classes: CT, LL, RL, PA and TA. Using a confusion matrix as a performance measure, a classification accuracy of 83.5% was achieved for the five-class fingerprint problem. Using Accept-Reject rates as a second performance measure, high average values were obtained for the TAR (85.08%) and the TRR (95.62%), while low values were obtained for the FAR (4.38%) and the FRR (14.92%).

The main advantage that the reported fingerprint classifier has over other structural classifiers is that it is able to make a decision in the presence of missing data. This is mainly because of the SCFR which provides a way of distinguishing the LL fingerprints from the RL fingerprints in the absence of the points of Delta. The DCFR also provides a way of correctly classifying CT fingerprints in the absence of one, two or even all the Deltas. An additional advantage it has is that it is able to defeat the structural limitation associated with the PA and TA fingerprints. The only disadvantage associated with the reported fingerprint classifier is that it solely relies on the module that detects the Core and the Delta. In the absence of this module, fingerprint classification becomes impossible.

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References

[1] A. K. Jain, S. Prabhakar and L. Hong, "A Multichannel Approach to Fingerprint Classification". IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 21, pp. 348-359, Apr 1999.

[2] A. K. Jain, S. Prabhakar, L. Hong and S. Pankanti, "FingerCode: A Filterbank for Fingerprint Representation and Matching". 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 2, pp 2187-2192, 1999.

[3] M. Bosque, Understanding 99% of Artificial Neural Networks. Writers Club Press, first edition, 2002.

[4] N. Cristianini and J. Shawe-Taylor, An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods, first edition, 2000.

[5] Y. Yao, G. L. Marcialis, M. Pontil, P. Frasconi and F. Roli, "Combining Flat and Structured Representations for Fingerprint Classification with Recursive Neural Networks and Support Vector Machines". Pattern Recognition, vol. 36, pp. 397406, 2003.

[6] D. Maltoni, D. Maio, A. K. Jain and S. Prabhakar, Handbook of Fingerprint Recognition. Springer, second edition, 2003.

[7] R. J. A. Little and D. B. Rubin, Statistical Analysis with Missing Data. New York: John Wiley, 1987.

[8] C. L. Phillips, J. M. Parr and E. A. Riskin, Signals, Systems and Transforms, Pearson Education Inc, Upper Saddle River, third edition, 2003.

[9] A. P. Fitz and R. J. Green, "Fingerprint Classification using a Hexagonal Fast Fourier Transform". Pattern Recognition, vol. 29, pp. 1587-1597, Feb 1996.

[10] C. V. K. Rao and K. Black, "Type Classification of Fingerprints: A Syntactic Approach". IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 02, pp. 223-231, Jun 1980.

[11] K. Karu and A. K. Jain, "Fingerprint Classification". Pattern Recognition, vol. 29, pp. 389-404, 1996.

[12] R. Cappelli, A. Lumini, D. Maio and D. Maltoni, "Fingerprint Classification by Directional Image Partitioning". IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 21, pp. 402-421, May 1999.

[13] R. Cappelli, D. Maio and D. Maltoni, "A Multi-Classifier Approach to Fingerprint Classification". Pattern Analysis & Applications, vol. 5, pp. 136-144, 2002.

[14] S. Wang, W. W. Zhang and Y. S. Wang, "Fingerprint Classification by Directional Fields". Fourth IEEE International Conference on Multimodal Interfaces, pp. 395-399, 2002.

[15] Q. Zhang and H. Yan, "Fingerprint Classification Based on Extraction and Analysis of Singularities and Pseudo Ridges", Pattern Recognition, vol. 37, pp. 2233-2243, 2004.