5

# On the Introduction of Secondary Fingerprint Classification

Ishmael S. Msiza[1], Jaisheel Mistry[1], Brain Leke-Betechuoh[1], Fulufhelo V. Nelwamondo[1,2] and Tshilidzi Marwala[2]
[1]*Biometrics Research Group, CSIR Modelling & Digital Sciences*
[2]*Faculty of Engineering & the Built Environment, University of Johannesburg*
*Republic of South Africa*

## 1. Introduction

The concept of fingerprint classification is an important one because of the need to, before executing a database search procedure, virtually break the fingerprint template database into smaller, manageable partitions. This is done in order to avoid having to search the entire template database and, for this reason, minimize the database search time and improve the overall performance of an automated fingerprint recognition system. The commonly used primary fingerprint classes add up to a total of five (Msiza et al., 2009):

- Central Twins (CT),
- Left Loop (LL),
- Right Loop (RL),
- Tented Arch (TA), and
- Plain Arch (PA).

Many fingerprint classification practitioners, however, often reduce these five fingerprint classes to four. This is, at a high level, due to the difficulty in differentiating between the TA and the PA class. These two similar classes are often combined into what is referred to as the Arch (A) class. Recent examples of practitioners that have reduced the five-class problem to a four-class problem include Senior (2001), Jain & Minut (2002), and Yao et al. (2003). The not so recent examples include Wilson et al. (1992), Karu & Jain (1996), and Hong & Jain (1998). These four primary classes are sufficient in the performance improvement of small-scale applications such as access control systems and attendance registers of small to medium-sized institutions. They, however, may not be sufficient in the performance improvement of large-scale applications such as national Automatic Fingerprint Identification Systems (AFIS). In order to enforce visible performance improvement on such large-scale applications, this chapter introduces a two-stage classification system, by taking advantage of the extensibility of the classification rules that utilize the arrangement of the fingerprint global landmarks, known as the singular points (Huang et al., 2007) (Mathekga & Msiza, 2009).
The first classification stage produces the primary fingerprint classes and then the second classification stage breaks each primary class into a number of secondary classes. It is

important to note that the concept of secondary fingerprint classification is one that has not been exploited by fingerprint classification practitioners, and is being formally introduced in this chapter for the first time. The next section presents a detailed discussion of both the primary and the secondary fingerprint classes.

## 2. Primary and secondary fingerprint classes

This section presents the proposed primary and secondary fingerprint classes, together with the rules used to determine them. It is important to note that the rules used to determine these primary and the secondary classes are based on the arrangement of the fingerprint singular points, namely, the fingerprint core and the fingerprint delta. Forensically, a fingerprint core is defined as the innermost turning point where the fingerprint ridges form a loop, while the fingerprint delta is defined as the point where these ridges form a triangulating shape (Leonard, 1988). Figure 1 depicts a fingerprint with the core and delta denoted by the circle and the triangle, respectively.


Fig. 1. A fingerprint showing clear markings of the core (circle) and the delta (triangle)

### 2.1 Central Twins (CT) primary class and its secondary classes

Fingerprints that belong to the CT class are, at a primary level, those that have ridges that either form (i) a circular pattern, or (ii) two loops, in the central area of the print. Some practitioners usually refer to the circular pattern as a whorl (Park & Park, 2005), while the two-loop pattern is referred to as a twin loop (Karu & Jain, 1996). The similarity, however, between the two patterns is that they both have cores located next to each other in the central area of the fingerprint, which is the main reason why Msiza et al. (2009) grouped these two patterns into the same class, called the Central Twins class. Figure 2(a) shows the whorl pattern, while the twin loop pattern is depicted on figure 2(b).

In addition to the two cores located in the central area, fingerprints belonging to CT class also have two deltas. These two deltas, however, are not located in the central area of the print, which immediately implies that there is a chance that one, or even both, may not be captured. All of this is dependent on how the user or subject impresses their finger, for capturing, on the surface of the fingerprint acquisition device. This is what brings into point the possibility of deriving secondary classes of this CT primary class.

The CT secondary classes derived in this chapter are depicted in figure 3, and they add up to a total of three. Figure 3(a) shows a CT class fingerprint that has all the singular points captured,

(a) Whorl pattern (b) Twin loop pattern

Fig. 2. Fingerprint patterns that collectively belong to the CT primary class. The whorl pattern has a circular structure that forms two cores, and the twin loop pattern has two loops that form two cores

two cores and two deltas, which is an ideal case. Such a complete capture of information normally occurs in applications where fingerprints are rolled, instead of being slapped. This is because of the fact that deltas, in fingerprints that belong to the CT primary class, are normally located adjacent to the edges of the fingerprint ridge area. A CT class fingerprint that has two cores and two deltas captured, is assigned to what is introduced as the CT-1 secondary class. A CT class fingerprint that has two cores and one delta, as shown in figure 3(b), is assigned to what is introduced as the CT-2 secondary class while the one that has two cores and no delta, as depicted in figure 3(c), is assigned to what is introduced as the CT-3 secondary class.

(a) CT-1 secondary class (b) CT-2 secondary class (c) CT-3 secondary class

Fig. 3. Fingerprint patterns that determine the CT secondary classes. CT-1 class: 2 cores & 2 deltas; CT-2 class: 2 cores & 1 delta; and CT-3 class: 2 cores & no delta

### 2.2 Arch (A) primary class and its secondary classes

Fingerprints that belong to the A class are, at a primary level, those that have ridges that appear to be entering the fingerprint on one side, rise in the middle area of the fingerprint, and leave the fingerprint on the opposite side, as depicted in figure 4. Figure 4(a) shows a fingerprint pattern that some practitioners normally classify as a plain arch, while figure 4(b) depicts a pattern that some practitioners classify as a tented arch. The technical report of Hong & Jain (1998) is one example of the practice of ordering these two patterns into separate classes. A year later, however, Jain et al. (1999) realized that there is often a mis-classification between the two patterns, hence it is better to combine them into one class. Many other practitioners, including Msiza et al. (2009), have observed that combining the plain arch and the tented arch patterns into one class, does improve the classification accuracy.

(a) Plain arch pattern (b) Tented arch pattern

Fig. 4. Fingerprint patterns that collectively belong to the A primary class. The plain arch pattern has no singular points while the tented arch pattern has a core and a delta, with the delta located almost directly below the core

Because of this reality, it is proposed that these two patterns are better off at a secondary level of fingerprint classification. This immediately provides a platform for the proposition of a number of A class secondary rules. An A class fingerprint that is without both a core and a delta, is assigned to what is introduced as the A-1 secondary class. Msiza et al. (2009) suggest that, for an A class fingerprint that has a core and delta detected, the absolute difference between their $x$-coordinates, $\Delta x$, is less than or equal to 30 pixels. It is, for this reason, proposed that if an A class fingerprint has a core and delta detected, and:

$$pixels\ 15 \leqslant \Delta x \leqslant 30\ pixels, \tag{1}$$

then the fingerprint is assigned to what is introduced as the A-2 secondary class, else if:

$$pixels\ 0 \leqslant \Delta x < 15\ pixels, \tag{2}$$

then fingerprint is assigned to what is introduced as the A-3 secondary class. Equation 2 is used for the instances where the rise of the ridges in the middle part of the fingerprint is extremely acute, hence $\Delta x$ is extremely small. Figure 5 depicts all three A secondary fingerprint classes.


(a) A-1 secondary class (b) A-2 secondary class (c) A-3 secondary class

Fig. 5. Fingerprint patterns that determine the A secondary classes. A-1 class: 0 cores & 0 deltas; A-2 class: equation 1; and A-3 class: equation 2

### 2.3 Left Loop (LL) primary class and its secondary classes

Fingerprints that belong to the LL class are, at a primary level, those that have ridges that appear to be entering the fingerprint on the left hand side, make a loop in the middle area of the fingerprint, and leave the fingerprint on the same side where they entered. The loop in the middle area is what forms the core of the print. An example of a fingerprint that belongs to this class is depicted on figure 6. In addition to the core that is formed by the loop in the middle area, an LL fingerprint has a delta located at the bottom of the loop, adjacent to the right hand side edge of the print. Depending on how the finger is impressed against the surface of the capturing device, there is always a chance that the delta may not be captured, more especially because it is adjacent to the edge of the fingerprint. This, therefore, presents an opportunity for the formulation of two LL secondary classes.

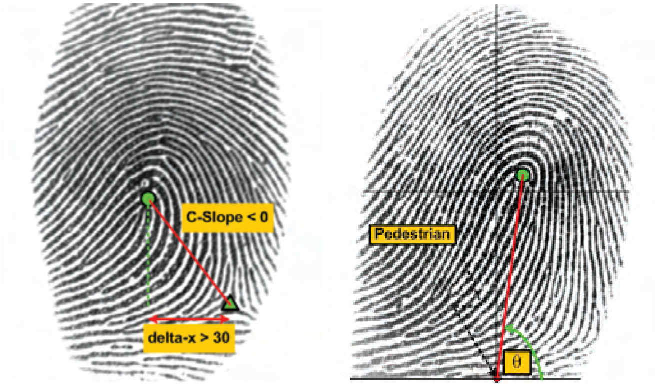
Fig. 6. A fingerprint pattern that belongs to the LL primary class. The ridges enter the print on the left hand side, make a loop in the middle, and leave on the same side

If a fingerprint that belongs to the LL class has (i) both a core and a delta detected, (ii) the conjugate slope (C-Slope) of the line joining the core and the delta is negative, and (iii) $\Delta x > 30$

pixels, then this fingerprint is assigned to what is introduced as the LL-1 secondary fingerprint class. The said C-Slope is just a complement of the conventional slope, because its reference point, or origin, is not the geometric center of the fingerprint image, but is the top left hand corner of the image. The LL-1 classification rules are summarized in figure 7(a).
If a fingerprint that belongs to the LL class has (i) only a core detected, and (ii) the auxiliary ($\theta$) is less than 90 degrees, then the fingerprint is assigned to what is introduced as the LL-2 secondary class. The auxiliary ($\theta$) is mathematically defined:

$$\theta = arctan(M) \tag{3}$$

where $M$ is the C-Slope of the line joining the core and the pedestrian point (Msiza et al., 2009). The pedestrian is a point located along the bottom of the fingerprint image, exactly below the True Fingerprint Center Point (TFCP), as shown in figure 7(b). Its $x$-coordinate is exactly the same as the one of the TFCP, and its $y$-coordinate has the same value as the height of the fingerprint image. The TFCP is defined as the geometric center of the fingerprint ridge area, that is, the fingerprint foreground (Msiza et al., 2011). Figure 7(b) shows the TFCP marked by the point of intersection of the two Cartesian axes.




(a) LL-1 secondary class (b) LL-2 secondary class

Fig. 7. Fingerprint patterns that determine the LL secondary classes. LL-1 secondary class: 1 core & 1 delta, with C-Slope $<$ 0; and LL-2 secondary class: 1 core & 0 delta, with $\theta < 90$ degrees

### 2.4 Right Loop (RL) primary class and its secondary classes

Fingerprints that belong to the RL class are, at a primary level, those that have ridges that appear to be entering the fingerprint on the right hand side, make a loop (which forms a core) in the middle area of the fingerprint, and leave the fingerprint on the same side where they entered. An example of a fingerprint that belongs to this RL class is depicted on figure 8. In addition to the core that is formed by the loop in the middle, an RL fingerprint has a delta located at the bottom of the loop, adjacent to the left hand side edge of the print. Similarly, depending on how the finger is impressed against the capturing device, there is always a chance that the delta may not be captured, more especially because it is adjacent to the edge of the fingerprint. This, therefore, presents an opportunity for the formulation of two RL secondary classes.

Fig. 8. A fingerprint pattern that belongs to the RL primary class. The ridges enter the print on the right hand side, make a loop in the middle, and leave on the same side

If a fingerprint that belongs to the RL class has (i) both a core and a delta detected, (ii) the C-Slope of the line joining the core and the delta is positive, and (iii) $\Delta x \leqslant 30$ pixels, then this fingerprint is assigned to what is introduced as the RL-1 secondary fingerprint class. If a fingerprint that belongs to the RL class has (i) only a core detected, and (ii) the auxiliary ($\theta$) is greater than or equal to 90 degrees, then the fingerprint is assigned to what is introduced as the RL-2 secondary fingerprint class. These two secondary classification rules are summarized in figure 9.


(a) RL-1 secondary class (b) RL-2 secondary class

Fig. 9. Fingerprint patterns that determine the RL secondary classes. RL-1 secondary class: 1 core & 1 delta, with C-Slope $> 0$; and LL-2 secondary class: 1 core & 0 delta, with $\theta \geqslant 90$ degrees

### 2.5 Classes overview

Following the proposed primary and secondary classes, figure 10 presents a combined picture that shows the relationship between all of them. The primary classification layer consists of 4 instances, while the secondary classification layer consists of a total of 10 instances.

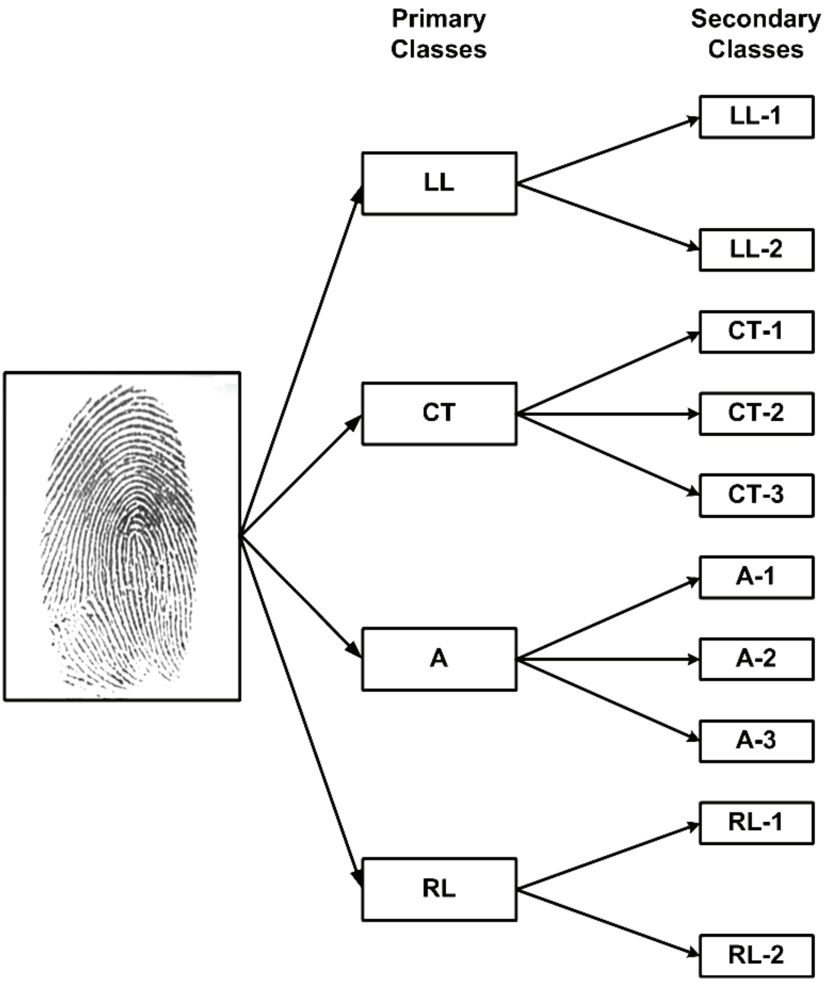



Fig. 10. An overview of the proposed primary and secondary fingerprint classes

## 3. Implementation of the proposed classification scheme

The implementability of the proposed classification scheme is demonstrated through the pseudo-code presented in algorithm 1. It is important to note that, before classification can be done, the captured fingerprint has to go through some pre-processing. These pre-processes include:

- contrast enhancement (Hong et al., 1998),
- ridge segmentation (Maltoni et al., 2009),
- orientation image computation and smoothing (Ratha et al., 1995), and
- singular point detection (Mathekga & Msiza, 2009).

The credibility of this proposed classification scheme is evaluated, in two different ways, in the next section.

**Algorithm 1:** The main procedure that, when presented with singular points, determines both a fingerprint's primary and secondary class

**Input** : Fingerprint singular points
**Output**: Fingerprint primary and secondary class

```
begin
    initialize: primary class = unknown, and secondary class = unknown;
    calculate: the number of cores, N_C, and the number of deltas, N_D, detected;
    if N_C = 0 and N_D = 0 then
        use algorithm 2 for classification;
    end
    else if N_C = 1 and N_D = 0 then
        use algorithm 3 for classification;
    end
    else if N_C = 1 and N_D = 1 then
        use algorithm 4 for classification;
    end
    else if N_C = 2 and N_D is between 0 and 2 then
        use algorithm 5 for classification;
    end
end
```

**Algorithm 2:** A procedure that, when presented with neither core nor delta, determines both a fingerprint's primary and secondary class

**Input** : Zero core and zero delta
**Output**: Fingerprint primary and secondary class

```
begin
    primary class = A;
    secondary class = A-1;
end
```

## 4. Classifier performance evaluation

In order to evaluate the credibility of the idea of secondary fingerprint classification, it is important to measure the accuracy of both the primary and the secondary classification module. If this idea is indeed credible, the difference between the accuracy value of the primary module and the one of the secondary module should be small. It should be small to an

**Algorithm 3:** A procedure that, when presented with one core and no delta, determines both a fingerprint's primary and secondary class

**Input** : One core and zero delta
**Output**: Fingerprint primary and secondary class

**begin**
    compute: the coordinates of the pedestrian;
    compute: the C-Slope, $M$, of the line joining the core and the pedestrian;
    compute: the auxiliary, $\theta$, using equation 3;
    **if** $\theta < 90$ *degrees* **then**
        primary class = LL;
        secondary class = LL-2;
    **end**
    **else if** $\theta \geqslant 90$ *degrees* **then**
        primary class = RL;
        secondary class = RL-2;
    **end**
**end**

extent that it should tempt any fingerprint classification practitioner to, in future applications, consider using the proposed secondary fingerprint classes as primary classes.

In addition to the accuracy values, the proposed classification scheme's credibility should be evaluated through observing the time it takes a fingerprint recognition system to search through a template database (i) without any classification, (ii) with only the primary classification module, and (ii) with the secondary classification module. For this classification scheme to be regarded as credible, the average database search time for cases (ii) and (iii) must be less than that for case (i), and the one for case (iii) should be less than the one for for case (ii), while the matching rates remain significantly unchanged. For the purposes of this evaluation, the CSIR-Wits Fingerprint Database (CWFD) which was jointly collected, for academic research purposes, by the Council for Scientific & Industrial Research (CSIR) and the University of the Witwatersrand (Wits), both in the Republic of South Africa.

### 4.1 Classification rates

This section presents the classification accuracy values, in the form of confusion matrices, of both the primary and the secondary classification modules. A confusion matrix is a table that shows a summary of the classes assigned by the automated fingerprint classifier, measured against those assigned by a human fingerprint classification expert. The classification accuracy value is mathematically expressed as:

$$Accuracy = \frac{M}{T} \times 100\%, \tag{4}$$

where $M$ is the sum of the main diagonal of the matrix, and $T$ is the sum of all the instances of data in the chosen database. Evaluated on a database that contains 946 instances, table 1 shows the confusion matrix for the primary classification module, while table 2 shows the confusion matrix of the secondary classification module.

**Algorithm 4:** A procedure that, when presented with one core and one delta, determines both a fingerprint's primary and secondary class

**Input** : One core and one delta
**Output**: Fingerprint primary and secondary class

```
begin
    compute: the absolute difference, Δx, between the x-coordinates;
    if Δx ⩽ 30 pixels then
        primary class = A;
        if Δx ⩽ 15 pixels then
            secondary class = A-2;
        end
        else if Δx < 15 pixels then
            secondary class = A-3;
        end
    end
    if Δx > 30 pixels then
        compute the C-Slope of the line joining the core and the delta;
        if C-Slope is Positive then
            primary class = RL;
            secondary class = RL-1;
        end
        else if C-Slope is Negative then
            primary class = LL;
            secondary class = LL-1;
        end
    end
end
```

Table 1 displays a classification accuracy of 80.4%, which is an acceptable figure for a four-class problem. As an example, Senior (1997) obtained a classification accuracy of 81.6% for his four-class problem. Some of the A class fingerprints are mis-classified as LL and RL because it is not all of them that have a $\Delta x$ that is less than 30 pixels. Possible future improvements, therefore, involve a bit more experimentation on a range of $\Delta x$ values. Some of the CT class fingerprints are mis-classified as A possibly because the singular point detection module was unable to detect the cores of the fingerprints. A possible future improvement, therefore, involves working on the functionality of the singular point detection module. Some of the LL class fingerprints are mis-classified as A because it is not all the LL fingerprints that have a $\Delta x$ that is greater than 30 pixels, and the same reasoning can be attributed to the mis-classification of some of the RL class fingerprints. Possible future improvements, again, involve a bit more experimentation on a range of $\Delta x$ values.

The secondary classification accuracy in table 2 has a value of 76.8%, which is an encouraging figure for a newly introduced concept. This implies that there is a difference of only 3.6% between the primary and the secondary classification modules. This, therefore, provides future opportunities for a classification practitioner to fine-tune the secondary classification

**Algorithm 5:** A procedure that, when presented with two cores and zero or a few deltas, determines both a fingerprint's primary and secondary class

**Input** : Two cores and zero or a few deltas
**Output**: Fingerprint primary and secondary class

```
begin
    primary class = CT;
    calculate: the exact number of deltas, N_D, detected;
    if N_D = 0 then
        secondary class = CT-3;
    end
    else if N_D = 1 then
        secondary class = CT-2;
    end
    else if N_D = 2 then
        secondary class = CT-1;
    end
end
```

| Actual | As | | | | |
|---|---|---|---|---|---|
| | A | CT | LL | RL | Total |
| A | **200** | 03 | 25 | 36 | 264 |
| CT | 18 | **187** | 05 | 10 | 220 |
| LL | 10 | 08 | **152** | 06 | 176 |
| RL | 29 | 11 | 24 | **222** | 286 |
| | | | 80.4% | | 946 |

Table 1. The primary class experimental results tested on the CWFD, which contains 946 instances of data

rules in order to further close down the gap between the two classification modules. As soon as this gap approaches zero, these newly introduced secondary classes can be used as primary classes and, with a total of 10 primary classes, there will be countless opportunities to further reduce the database search time. This is achievable through the introduction of another set of secondary classes by using unsupervised techniques such as artificial neural networks (Marwala, 2007).

### 4.2 Average search times and matching rates

To further demonstrate the credibility of the proposed classification scheme, this section presents its performance when measured through the average database search time, together with the matching rates, also done on the CWFD. These matching rates are listed as follows:

- True Match Rate (TMR)
- False Match Rate (FMR)
- True Non-Match Rate (TNMR)

| Actual | As | | | | | | | | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | A-1 | A-2 | A-3 | CT-1 | CT-2 | CT-3 | LL-1 | LL-2 | RL-1 | RL-2 | |
| A-1 | **118** | 01 | 01 | 00 | 00 | 03 | 03 | 05 | 00 | 23 | 154 |
| A-2 | 05 | **17** | 02 | 00 | 00 | 00 | 02 | 01 | 00 | 05 | 33 |
| A-3 | 06 | 02 | **48** | 00 | 00 | 00 | 05 | 09 | 00 | 08 | 77 |
| CT-1 | 00 | 00 | 00 | **00** | 00 | 00 | 00 | 00 | 00 | 00 | 00 |
| CT-2 | 03 | 00 | 00 | 00 | **16** | 03 | 00 | 00 | 00 | 00 | 22 |
| CT-3 | 14 | 00 | 01 | 00 | 07 | **161** | 00 | 05 | 01 | 09 | 198 |
| LL-1 | 00 | 00 | 00 | 00 | 00 | 00 | **09** | 00 | 00 | 02 | 11 |
| LL-2 | 07 | 03 | 00 | 00 | 03 | 05 | 03 | **140** | 01 | 03 | 165 |
| RL-1 | 02 | 00 | 00 | 00 | 00 | 00 | 00 | 00 | **09** | 00 | 11 |
| RL-2 | 24 | 03 | 00 | 00 | 00 | 11 | 02 | 22 | 04 | **209** | 275 |
| | | | | | | 76.8% | | | | | 946 |

Table 2. The secondary class experimental results tested on the CWFD, which contains 946 data instances

- False Non-Match Rate (FNMR)

A true match occurs when a fingerprint recognition system correctly regards a genuine comparison, $C_G$, as genuine. Given a matching threshold $T$, the TMR value of $T$ is the number of genuine comparisons with match scores greater than $T$, divided by the total number of genuine samples, $S_G$, presented for comparison. Mathematically, this is modeled as:

$$TMR = \frac{Count\{C_G \geqslant T\}}{S_G} \times 100\%. \tag{5}$$

A false match occurs when a fingerprint recognition system regards an impostor comparison, $C_I$, as genuine. The FMR value of $T$ is the number of impostor comparisons with match scores greater than $T$, divided by the total number of impostor samples, $S_I$, presented for comparison. Mathematically, the FMR can be modeled as:

$$FMR = \frac{Count\{C_I \geqslant T\}}{S_I} \times 100\%. \tag{6}$$

A true non-match occurs when a fingerprint recognition system correctly regards an impostor comparison as an impostor. The TNMR value of $T$ is the number of impostor comparisons with match scores less than $T$, divided by the total number of impostor samples presented for comparison. Mathematically, this can be modeled as:

$$TNMR = \frac{Count\{C_I < T\}}{S_I} \times 100\%. \tag{7}$$

A false non-match occurs when the fingerprint recognition system regards a genuine comparison as an impostor. The FNMR value of $T$ is the number of genuine comparisons with match scores less than $T$, divided by the total number of genuine samples presented for comparison. Mathematically, this can be modeled as:

$$FNMR = \frac{Count\{C_G < T\}}{S_G} \times 100\%. \quad (8)$$

Table 3 shows the results obtained from the evaluation, where 3 instances of the same fingerprint were enrolled into the template database, in order to make the system more accurate. The template database, for this reason, ended up with a total of $3 \times 86 = 258$ instances. The credibility of the proposed classification scheme is verified by the fact that the average database search time (AST) is improved from 2 426 ms to 645 ms and 492 ms by the primary and the secondary classification module, respectively, while the matching rates remain significantly unchanged.

| | No Classification | Primary Classification | Secondary Classification |
|---|---|---|---|
| True Match Rate (TMR) | 78.3% | 70.4% | 66.2% |
| False Match Rate (FMR) | 0.7% | 0.2% | 0.1% |
| True Non-Match Rate (TNMR) | 99.3% | 99.1% | 99.2% |
| False Non-Match Rate (FNMR) | 21.6% | 32.2% | 30.2% |
| Average Search Time (AST) | 2 426 ms | 645 ms | 492 ms |

Table 3. A summary of the match and non-match rates together with the average database search times, tested on the CWFD

Because the TMR and the FNMR are complements of each other, their values should add up to a 100%. For the same reason, the values of the FMR and the TNMR should add up to a 100%. The reason why this is not case in the third and the fourth columns of table 3 is that the database search was done continuously per group of fingerprint instances of a common subject, which leads to a loss of data. This loss of data is, in essence, attributable to a combination of possible mis-classifications and failure to meet the matching threshold.

## 5. Discussions and conclusions

This chapter presented the concept of automatic fingerprint classification, in general, and introduced the concept of secondary fingerprint classification, in particular. Secondary fingerprint classification was introduced in order to further reduce the time it takes for an automated fingerprint recognition system to search through a database of templates. The key fingerprint features employed in the proposed classification scheme are the core and the delta, with a total of 4 primary fingerprint classes; namely: CT, A, LL, and RL; and 10 secondary fingerprint classes, namely: CT-1, CT-2, CT-3, A-1, A-2, A-3, LL-1, LL-2, RL-1, and RL-2. Using a confusion matrix as a performance measure, the primary fingerprint classification module registered an accuracy of 80.4%, while the secondary classification module registered an accuracy of 76.8%. This 3.6% gap is indicative of the fact that, in future applications, there is a chance to fine-tune the secondary classification rules and, after improving the accuracy, there is even a good chance to use these secondary classes at a primary level. With a total of 10 fingerprint classes at a primary level, there is a good chance of decreasing the database search time even further, while the change in matching rates remains acceptably small.

## 6. References


Hong, L. & Jain, A.K. (1998). Classification of Fingerprint Images. *Michigan State University (MSU) Technical Report*, Jan. 1998, MSUCPS: TR98-18

Hong, L.; Wan, Y. & Jain, A.K. (1998). Fingerprint Image Enhancement: Algorithm and Performance Evaluation. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, Vol. 20, No. 08, Aug. 1998, pp. 777–789, ISSN: 0162-8828

Huang, C-Y.; Liu, L-M. & Douglas Hung, D.C. (2007). Fingerprint Analysis and Singular Point Detection. *Pattern Recognition Letters*, Vol. 28, No. 04, Apr. 2007, pp. 1937–1945, ISSN: 0167-8655

Jain, A.K.; Prabhakar, S. & Hong, L. (1999). A Multichannel Approach to Fingerprint Classification. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, Vol. 21, No. 04, Apr. 1999, pp. 348–359, ISSN: 0162-8828

Jain, A.K. & Minut, S. (2002). Hierarchical Kernel Fitting for Fingerprint Classification and Alignment, *Proceedings of the* 16$^{th}$ *International Conference on Pattern Recognition - Volume* 2, pp. 469–473, ISBN: 0-7695-1695-X, Quebec, Canada, Aug. 2002

Karu, K. & Jain, A.K. (1996). Fingerprint Classification. *Pattern Recognition*, Vol. 29, No. 03, Mar. 1996, pp. 389–404, ISSN: 0031-3203

Leonard, B. (1988). *Science of Fingerprints: Classification and Uses*, Diane Publishing Co., ISBN: 0-16-050541-0, Darby, Pennsylvania

Maltoni, D.; Maio, D.; Jain, A.K. & Prabhakar, S. (2009). *Handbook of Fingerprint Recognition*, Springer, ISBN: 978-84882-253-5, London, UK

Marwala, T. (2007). Bayesian Training of Neural Networks Using Genetic Programming. *Pattern Recognition Letters*, Vol. 28, No. 12, Dec. 2007, pp. 1452–1458, ISSN: 0167-8655

Mathekga, M.E. & Msiza, I.S. (2009). A Singular Point Detection Algorithm Based on the Transition Line of the Fingerprint Orientation Image, *Proceedings of the* 20$^{th}$ *Annual Symposium of the Pattern Recognition Association of South Africa*, pp. 01–06, ISBN: 978-0-7992-2356-9, Stellenbosch, South Africa, Nov. 2009

Msiza, I.S.; Leke-Betechuoh, B.; Nelwamondo, F.V. & Msimang, N. (2009). A Fingerprint Pattern Classification Approach Based on the Coordinate Geometry of Singularities, *Proceedings of the IEEE International Conference on Systems, Man & Cybernetics*, pp. 510–517, ISBN: 978-1-4244-2793-2, San Antonio, Texas, Oct. 2009

Msiza, I.S.; Leke-Betechuoh, B. & Malumedzha, T. (2011). Fingerprint Re-alignment: A Solution Based on the True Fingerprint Center Point, *Proceedings of the IEEE International Conference on Machine Learning & Computing – Vol.* 2, pp. 338–343, ISBN: 978-1-4244-9253-4, Little India, Singapore, Feb. 2011

Park, C.H. & Park, H. (2005). Fingerprint Classification Using Fast Fourier Transform and Nonlinear Discriminant Analysis. *Pattern Recognition*, Vol. 38, No. 04, Apr. 2005, pp. 495–503, ISSN: 0031-3203

Ratha, A.K.; Chen, S. & Jain, A.K. (1995). Adaptive Flow Orientation-Based Feature Extraction in Fingerprint Images. *Pattern Recognition*, Vol. 28, No. 11, Nov. 1995, pp. 1657–1672, ISSN: 0031-3203

Senior, A. (1997). A Hidden Markov Model Fingerprint Classifier, *Conference Record of the Thirty-First Asilomar Conference on Signals, Systems, & Computers*, pp. 306–310, ISBN: 0-8186-8316-3, Pacific Grove, California, Nov. 1997

Senior, A. (2001). A Combination Fingerprint Classifier. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, Vol. 23, No. 10, Oct. 2001, pp. 1165–1174, ISSN: 0162-8828

Wilson, C.L.; Candela, G.T.; Grother, P.J.; Watson, C.I. & Wilkinson R.A. (1992). Massively Parallel Neural Network Fingerprint Classification System. *National Institute of Standards and Technology (NIST) Technical Report*, Jan. 1992, NISTIR 4880

Yao, Y.; Marcialis, G.; Pontil, M.; Frasconi, P. & Roli, F. (2003). Combining Flat and Structured Representations for Fingerprint Classification with Recursive Neural Networks and Support Vector Machines. *Pattern Recognition*, Vol. 36, No. 02, Feb. 2003, pp. 397–406, ISSN: 0031-3203