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Toward An Efficient Fingerprint Classification

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1. Introduction

Biometrics technology is keep growing substantially in the last decades with great advances in biometric applications. An accurate personal authentication or identification has become a critical step in a wide range of applications such as national ID, electronic commerce, and automated and remote banking. The recent developments in the biometrics area have led to smaller, faster, and cheaper systems such as mobile device systems. As a kind of human biometrics for personal identification, fingerprint is the dominant trait due to its simplicity to be captured, processed, and extracted without violating user privacy.

In a wide range of applications of fingerprint recognition, including civilian and forensics implementations, a large amount of fingerprints are collected and stored everyday for different purposes. In Automatic Fingerprint Identification System (AFIS) with a large database, the input image is matched with all fields inside the database to identify the most potential identity. Although satisfactory performances have been reported for fingerprint authentication (1:1 matching), both time efficiency and matching accuracy deteriorate seriously by simple extension of a 1:1 authentication procedure to a 1:N identification system (Manhua, 2010). The system response time is the key issue of any AFIS, and it is often improved by controlling the accuracy of the identification to satisfy the system requirement. In addition to developing new technologies, it is necessary to make clear the trade-off between the response time and the accuracy in fingerprint identification systems. Moreover, from the versatility and developing cost points of view, the trade-off should be realized in terms of system design, implementation, and usability.

Fingerprint classification is one of the standard approaches to speed up the matching process between the input sample and the collected database (K. Jain et al., 2007). Fingerprint classification is considered as indispensable step toward reducing the search time through large fingerprint databases. It refers to the problem of assigning fingerprint to one of several pre-specified classes, and it presents an interesting problem in pattern recognition, especially in the real and time sensitive applications that require small response time. Fingerprint classification process works on narrowing down the search domain into smaller database subsets, and hence speeds up the total response time of any AFIS. Even for

fingerprint recognition, a large number of classification methods have been proposed (summarized in Section 2).

This chapter proposes a novel method for fingerprint classification using simple and established image processing techniques. The processing time of the proposed method is dramatically decreased with a small effect on the resulted classification accuracy. The processing time and the accuracy of the proposed classification method have been evaluated by intensive experiments over different standard fingerprint databases. The time-accuracy optimization is not trivial task for every biometrics based practical systems from theoretical to practical implementations of the classification algorithm. For example, selecting extremely complex features for performing classification might increase the processing time in a pattern matching, and hence, reducing the overall system performance. The total accuracy of any identification system depends on the distribution of the features in addition to the classification accuracy.

In the rest of this chapter, first we shade light on the existing classification methods. In common, fingerprint classification algorithms extract features from the interleaved ridge and valley flows on fingerprints. In terms of the previous features, fingerprints are classified by Sir Henry (Maltoni et al., 2009) into the common five classes, Arch, Tented Arch, Left Loop, Right Loop, and Whorl. One of the standard approaches for fingerprint classification is to use the information extracted by frequency domain analysis of input images. Some standard calculations on frequency domain are well studied, hence we can benefit from the refined algorithms and Application Specific Integrated Circuit (ASIC) for implementation. Our algorithm works different from any other approach in the literature by dividing a fingerprint image into four sub-images, and then applies the standard frequency-based algorithm to each sub images to extract distinguished feature based on ridge *(periodicity and directionality)* inside each sub image. Then, the classification process uses those extracted features to exclusively classify it into four classes (Tented Arch is regarded as Arch). We have implemented the algorithm, evaluated its processing time and classification accuracy on two standard databases.

The contribution of this chapter falls under the possibility to maximize time-accuracy trade-off by implementing simple techniques to build an effective fingerprint classification. The novelty of the classification method falls under the extraction of distinguished patterns from frequency domain representation of the fingerprint. Due to its simplicity, it is expected that the method may be combined with other advanced technologies such as machine learning (Yao et al., 2003) to improve both its robustness and efficiency.

2. Review of fingerprint classification

Fingerprint classification is still a hot research topic in the area of biometric authentication. Generally, the advantage of classification is that it provides an indexing mechanism and facilities the matching process over the large databases. Without a robust classification algorithm, identification performs exhaustive matching processes to an input with all of the available elements in the database, which is computationally demanding. Fingerprint classification is usually based on global features such as global ridge structure and core or delta singular points. The core point is defined as the topmost point of the innermost curving ridge, where the delta point is defined as the centre of triangular regions where three different direction flows meet (Espinosa-Dur, 2001).
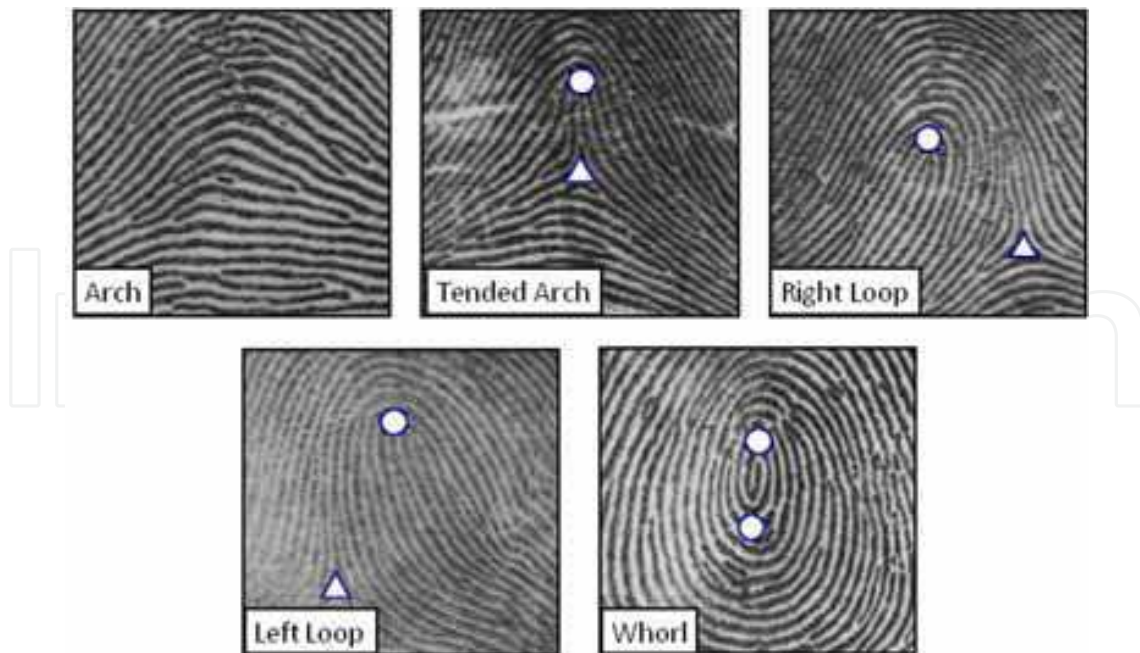
Fig. 1. Common five classes of fingerprints with singular points *(Circle-Core, Triangle-Delta)*

Fingerprint classification methods can be grouped into two main categories: continuous classification and exclusive classification (Maltoni et al., 2009). Figure 1 shows examples of exclusive fingerprint classes with related singular core and delta points (Amin & Neil, 2004).

2.1 Continuous fingerprint classification

In general, continuous classification overcomes some defects of exclusive classification by representing each fingerprint by a vector which summarizing its main features, instead of assigning them into a single class. (Lumini et al., 1997) proposed a continuous classification scheme which characterizes each fingerprint with a numerical vector. Apparently, continuous classification does not allow some tasks to be executed such as fingerprint labelling according to a given classification scheme. The continuous classification approach is more preferable than the classical exclusive approach if we want to classify fingerprints only for improving the fingerprint retrieval efficiency.

2.2 Exclusive fingerprint classification

Exclusive fingerprint classification groups fingerprint images into some predefined classes according to their global features. Most of fingerprint identification systems use that exclusive fingerprint classification approach (Cappelli et al., 1999) to improve the total response time. Global patterns of ridges and furrows in the central region of the fingerprint form special configuration, see Figure 1, which have a certain amount of intraclass variability. These variations are sufficiently small which allows a systematic classification of fingerprint (Wang et al., 2006). Galton (K. Jain et al., 2007) has made the first scientific studies on fingerprint classification area. He exclusively divided fingerprint into three major classes: Loop, Arch, and Whorl. Galton's algorithm is then refined by increasing the number of classes into eight classes: Plain Arch, Tended Arch, Right Loop, Left Loop, Plain Whorl, Central Pocket, Twin Loop, and Accidental Whorl.

Arch is a special type of fingerprint configuration, as less than 5% of all fingerprints is arches. Plain Arch is defined as a "type of fingerprint in which ridges enter one side and

flow out of the other with the rise of wave in the center". In Tended Arch, most of the ridges enter one side and flow out of the other with rise wave in the center and the rest of the ridges form a definite angle (Maltoni et al., 2009). Arch and Tended Arch classes are grouped into one class due to the small intra-class variations. Loop class is defined as a "type of fingerprints in which one or more of the ridges enter on fingerprint side, recurve, and touch or pass an imaginary line drawn from the delta to the core, and terminate or tend to terminate on or toward the same side from which such ridge or ridges entered" (Maltoni et al., 2009). A Whorl is "that type of fingerprint in which at least two deltas are present with a recurve in front of each". However, these preceding definitions are very general, but they catch the essence of the category. The performance of the exclusive classification strongly depends on the number of classes and the distribution of fingerprints. Unfortunately, in exclusive system the number of classes is small and fingerprints are not uniformly distributed. Also there are many ambiguous fingerprints whose exclusive classes that can not reliably be stated even by human experts. Exclusive classification allows the efficiency of the 10-print based identification to be improved, since the knowledge of the classes of the ten fingerprints can be used as a code for limiting the number of minutiae comparisons.

2.2.1 Graph based classifications

Graph based method, represented in Figure 2, is an example of spatial domain based classifiers. The basic idea of graph based classification scheme is partitioning the directional fingerprint image into homogenous regions, and these regions and the relations among them contain information useful for classification. The approach in (Maltoni & Maio, 1996) is divided into four main steps: computation of the directional image, segmentation of the directional image, construction of the relational graph, and the graph matching process. The relational graph is built by creating a node for each region and an arc for each pair of adjacent regions. Produced graph structure summarizes the topological features of the fingerprint by appropriately labeling the nodes and arcs of the graph. Although graph based approaches have interesting properties such as robustness to image rotation, displacement, and its ability to handle partial fingerprints, it is not easy to accurately partition the orientation image into homogeneous regions, especially in a poor quality fingerprint images. Producing good directional fingerprint image also needs preprocessing, binarization, and thinning which are time exhaustive operations that may impose impact on the overall system performance.

2.2.2 Dynamic mask approach

(Cappelli et al., 1999) have extended the graph based method, explained in the preceded paragraph, using dynamic mask approach that controls the freedom of fingerprint image segmentation process. A set of dynamic masks, directly derived from the most dominant fingerprint classes, are used to guide the image partitioning process. For every input fingerprint image, an application cost function is calculated for each dynamic mask. Intuitively, the application cost function measures how well mask fits with the input fingerprint image. A dynamic mask is built for only five fingerprint classes: Arch, Left Loop, Right Loop, Tented Arch, and Whorl. The smaller cost function value is the closer to the true fingerprint class.

There are many fingerprint classifications described in the literature (Maltoni et al., 2009). They can be grouped based on the used features and the type of the proposed classifiers.
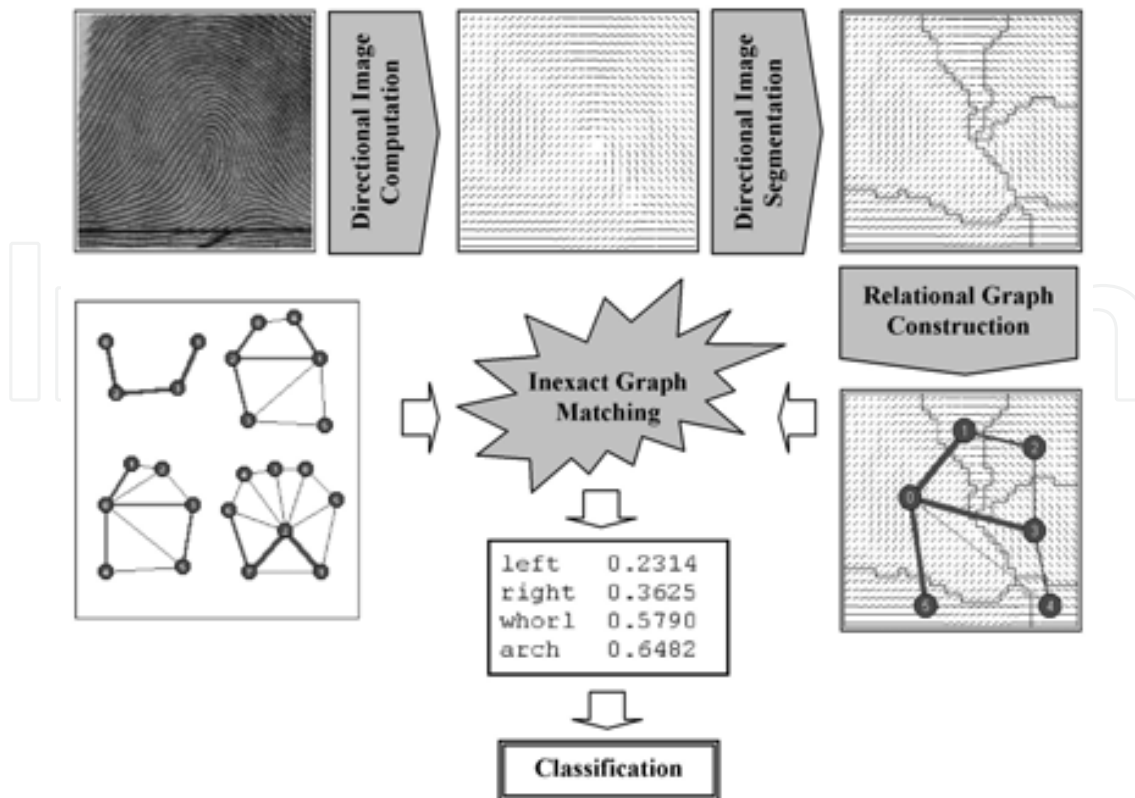
Fig. 2. Flowchart of graph based fingerprint classification technique, (Maltoni & Maio, 1996)

The most important types of classification techniques include Neural Network classifiers as in (Senior, 2001; Wang et al., 2006), the statistical based approach can be found in (Cappelli et al., 2002; K. Jain & Minut, 2002; Yao et al., 2003), and the rule-based classification approaches (K. Jain et al., 1999) that may use the numbers and relations of the singular points as a base for fingerprint classification process.

3. An efficient fingerprint classification

The proposed novel classification method is presented in this section. There are some classification methods exist which apply the idea of Fast Fourier Transform (FFT) to extract features from fingerprint images such as (Green & Fitz, 1996), (Sarbadhikari et al., 1998), and (Park & Park, 2005). These methods used the frequency representation of the full fingerprint image in the classification process. However, these methods come with a new idea, but they failed to achieve good results because the classes overlapping. The proposed method is novel and overcomes the classes overlapping problem, it also facilitates the texture property of fingerprint image by building four different patterns for each class using image division process. The main idea behind our method is that fingerprint images are divided into four sub-images, and then a standard FFT is applied to each sub-image to extract the class discriminant features. The prototype of the proposed algorithm can found in (Awad et al., 2008).

3.1 Outline
In our method, we consider classification of fingerprint images with four classes, Arch, Left Loop, Right Loop, and Whorl. The novel method consists of the following stages; Figure 3 introduces the algorithm flowchart that descries the following steps:

1. Calculation of standard classes patterns (four selected classes from a given database),
2. Acquisition of the input fingerprint image,
3. Division of the input image into four sub-images,
4. Transformation of the sub-images into frequency domain,
5. Patterns extraction for the input image,
6. Matching of the calculated pattern with the standard patterns calculated in step (1),
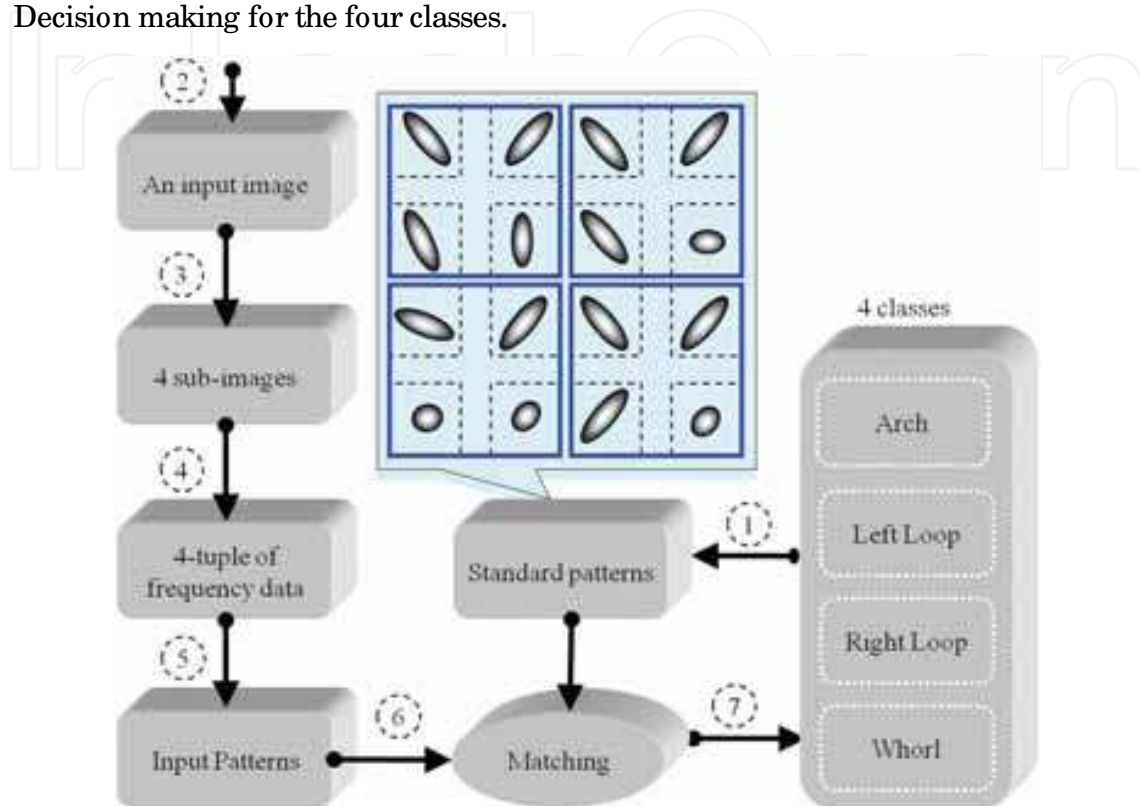7. Decision making for the four classes.

Fig. 3. Block diagram of patterns based fingerprint classification algorithm

The classification algorithm supports input fingerprint image in different formats, and the images size can be up to *(512 × 512)* pixels. Since the algorithm is an exclusive classifier the input image will be matched only with the standard classes to detect the correct class. The proposed algorithm can easily accept shifted, rotated, and even the poor quality images.

3.2 Division of Fingerprint image

At step (3), the input image is divided into four sub-images (a sub-image is sometimes called a "block" in the rest of this chapter) based on *(x, y)* lengths. Figure 4 shows an example of the division process. Fingerprint partitioning provides the ability to process fingerprint image as four different blocks with its own ridge frequency and direction. The number of blocks (four) has been selected due to processing time and computational complexity considerations. Four blocks selection compromising the trade-off between processing time and accepted algorithm's performance. Although the accuracy and the processing time of a classification method depend on the patterns (features) and the procedure of matching in general, roughly speaking, it is expected that the accuracy is better, but the processing time is get worse when the number of the sub images is being increased.
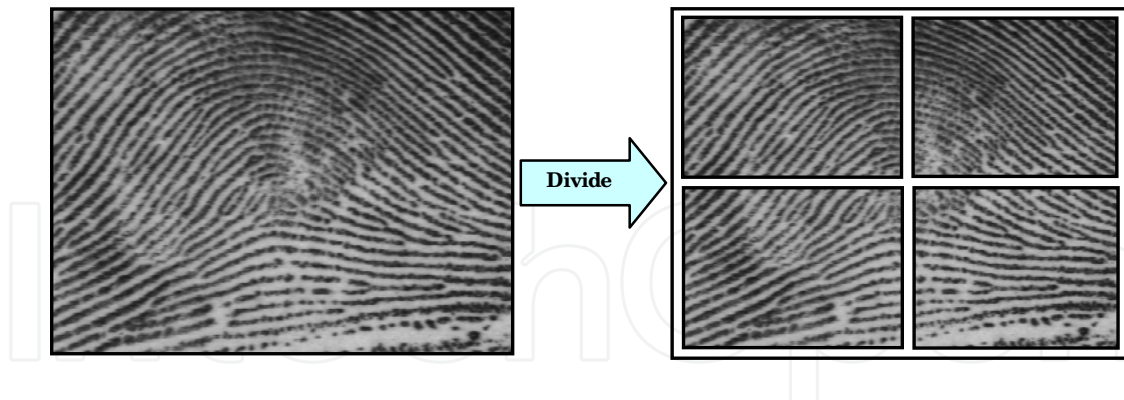
Fig. 4. A divided fingerprint image into four blocks (Input image was Arch)

3.3 Transformation into frequency domain

The simplest method to transform fingerprint images from spatial domain to frequency domain is 2D-FFT (Gonzalez et al., 2009). The FFT-based approach for estimating the frequency and direction of an image is an established method (Sherlock et al., 1994; Sarbadhikari et al., 1998; Park & Park, 2005; Gonzalez et al., 2009). In general, fingerprints have a definite periodicity of ridges or valleys, therefore the periodicity and directionality of ridges obtained by FFT could be a quantifier of the fingerprint texture in different directions. For the various fingerprint classes, FFT components are likely to be different. Moreover, since these frequency features are global in nature, they are likely to be less sensitive to shift, rotation, and noise. In our method, a 2D-FFT is applied individually to each sub-image. Since the ridge's direction and frequency of the fingerprint image are not constant in overall image, they will be different from one block to another. The key issue of the proposed method is to use these distinguished outputs to generate patterns for matching with the standard classes. We found the combinations of the frequency patterns of four blocks which realize a classification into the four common fingerprint classes. Figure 5 shows the FFT representation of all sub-images of a fingerprint in the Arch class. The frequency pattern in each block is clearly observed as a different pattern from the others in the senses of the size and the direction. These patterns will be extracted from FFT images in the next step.
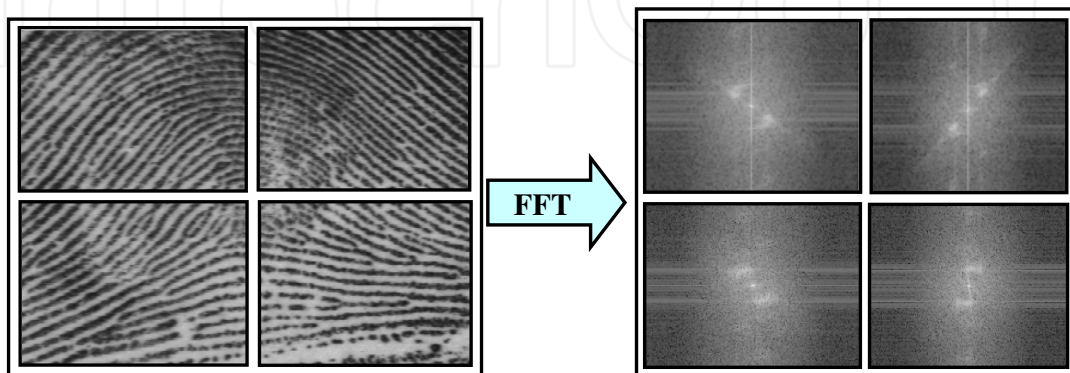

Fig. 5. Frequency domain representation for each sub image using 2D-FFT

3.4 Extraction of frequency patterns

Patterns extraction is the most important stage in our proposed classification method. The pattern of each class is constructed from the FFT outputs of four sub-images; therefore, the pattern of a single image is a 4-tuple of patterns. First, standard patterns of the four standard classes are extracted once and stored in a system buffer. The calculation of the standard patterns is based on the direction and shape of the FFT output. By considering the combination of 4 patterns, the proposed method achieves an accurate classification results. In the matching stage the system compares the 4-tuple of patterns of an input image with the 4-tuples of the standard classes. Figure 6 shows the frequency representation of the four fingerprint classes.

In this chapter, we considered simply the image of the FFT output as a frequency pattern. However, there is scope for further study about the representation of the pattern. We describe an idea of the representation in the rest of this subsection. In the pattern extraction, we considered that the output of FFT can be affected by three parameters: (i) ridge direction, (ii) ridges frequency or pitch, and (iii) the brightness variation in the block. The direction of output frequency is perpendicular to the total ridges direction in the block, while the ridge frequency appears in the frequency representation as a white spots on the line, the distance between these spots are inversely proportional to the ridges frequency. The pattern extraction process may consist of the following steps:

• Numbering each block,
• Computing the frequency orientation, and
• Deriving the output shape of FFT using simple morphological operations.

Figure 7 shows an example of the expected patterns corresponds to the FFT output in Figure 6.

3.5 Patterns matching

As we mentioned in the previous subsection, each element of the 4-tuple for a pattern is an image of the FFT output. Pattern padding process guarantees that the image is *(300 × 300)* pixels. We implemented the pattern matching of blocks by two methods, the absolute image difference and the 2D image correlation. To confirm that the two methods should be able to recognize each class, we operated prior experiments for the both methods.

3.5.1 Difference-based matching

The output of the matching process is held as a matrix with the same dimensions of the block used in matching process, that is, the matrix has the *(300 × 300)* elements. Figure 8 and Figure 9 both show a part of the results of the comparison based on the absolute image difference. Figure 8 is for the comparison of a Whorl pattern with the standard patterns of the four classes, where Figure 9 is of a random image.

We selected only the maximum values inside the matrix to show the results in appreciate format. Full patterns matching produces result that makes the decision maker able to classify different input images into its appreciating classes. In the graphs, the horizontal axis shows the columns of the output matrix, where we selected only the maximum values inside the matrix to show the results in appreciate format, therefore the length is come to 150. The vertical axis shows the summation of the elements of each column for the four blocks, that is, the total of the *(300 × 4)* elements. By the result, we can see that the difference-based matching is applicable for the pattern marching.
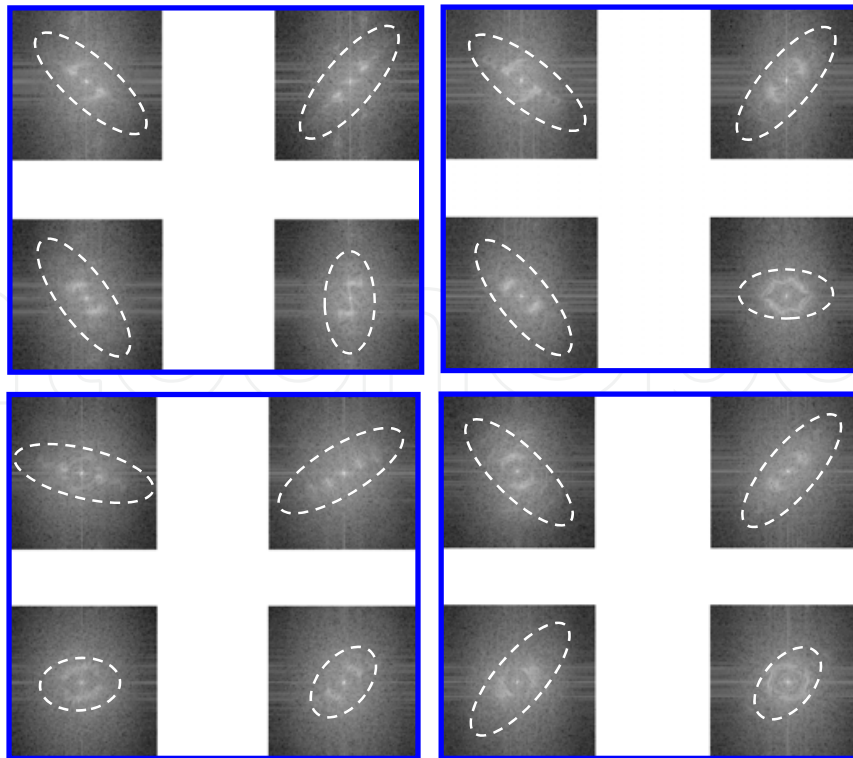
Fig. 6. Frequency transformation for each class (up left (Arch), up right (Left Loop), down left (Right Loop), down right (Whorl))
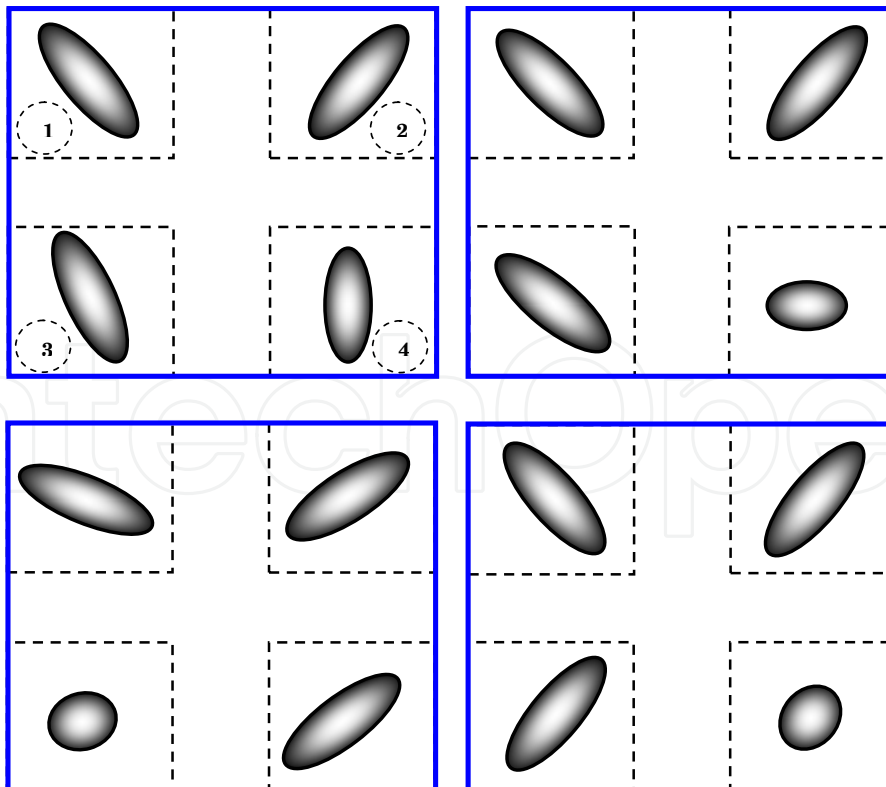

Fig. 7. The patterns extracted from sub images in Figure 6. Numbers inside the dashed circles are representing the block order
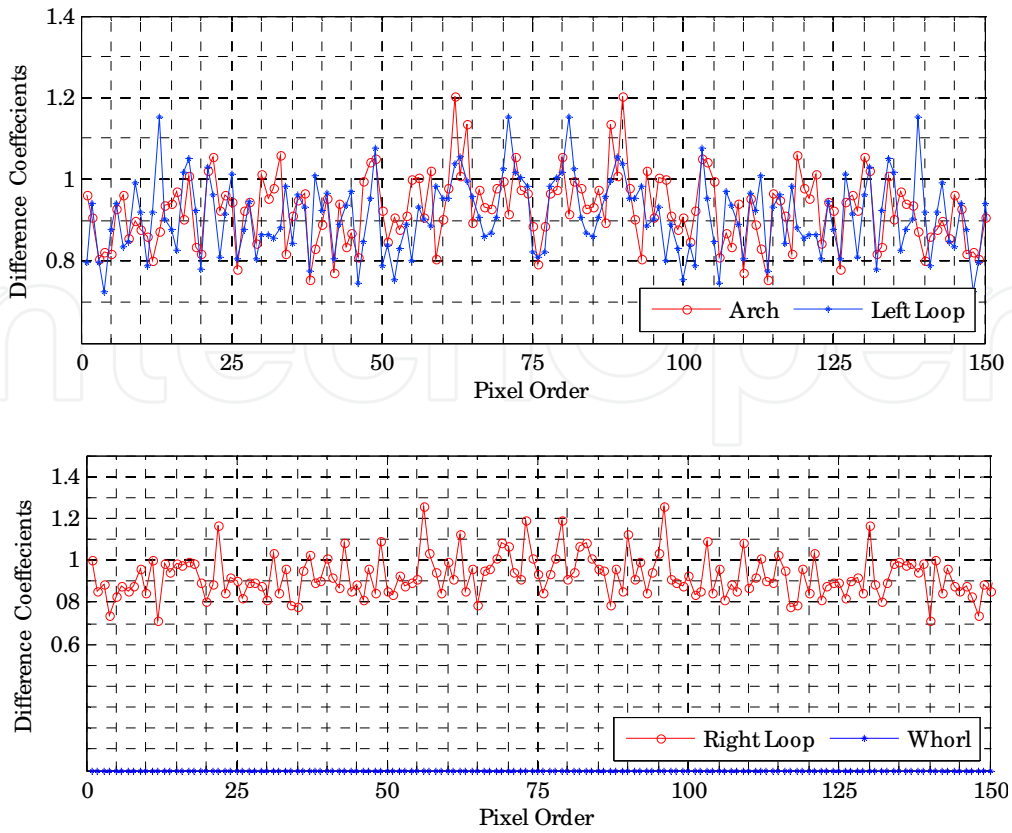
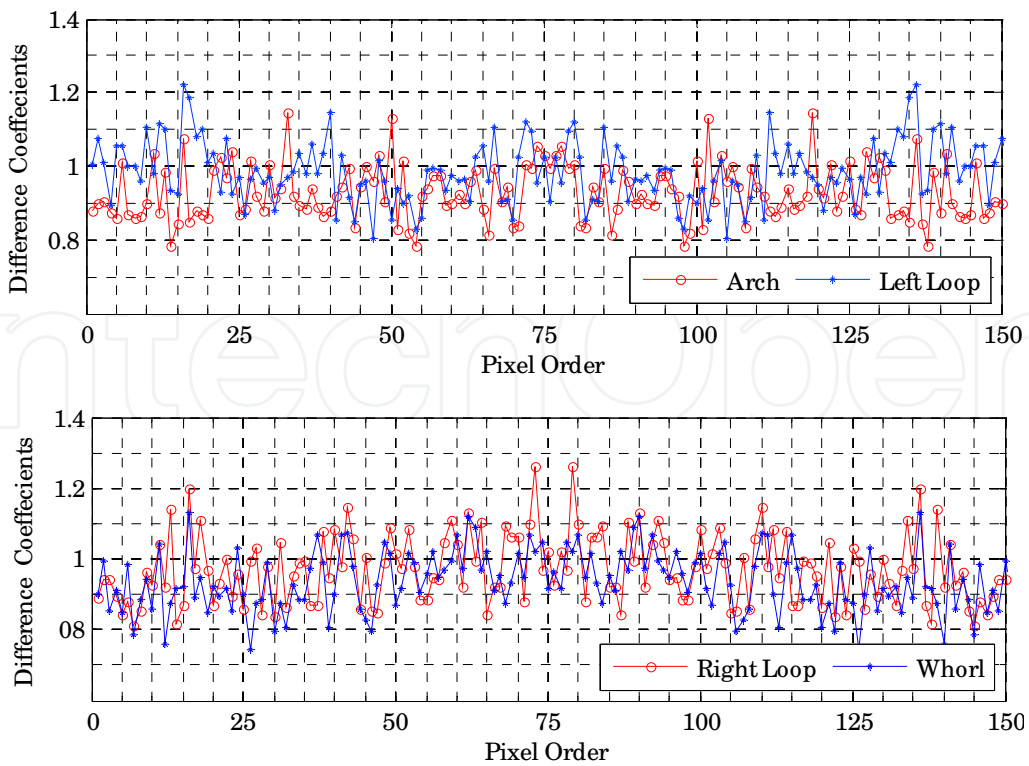Fig. 8. Difference between the standard patterns and a Whorl patterns

Fig. 9. Difference between the standard patterns and a random input pattern (Arch)

3.5.2 Correlation-based matching

Image correlation is much easier especially in frequency domain. The key issue of our proposed algorithm is the response time. We conducted intensive experimental work on performing pattern matching in frequency domain to make the processing time as short as possible. Comparing to image difference method, image correlation give a shorter response time with high matching accuracy. Also, the output data of the correlation process is little and it could be plotted or represented easily. Figure 10 and Figure 10 both are the result of the comparisons with the standard pattern with a Whorl pattern and a random pattern, respectively. In the graphs, "Block Number" is the number for the order of the four sub-images, (1), (2), (3), and (4) for up left, up right, down left, and down right, respectively. By the result, we can see that the correlation-based matching is also applicable for the patterns matching.

3.6 Decision making

The decision maker is responsible for selecting the final class from the information provided by the pattern matching stage. As we mentioned before, the matching results are stored in a matrix, and we use only the maximum matching values to preserve memory and plot the results in acceptable format. In the experiments in the following section, we considered the simple total of the elements of the matrix. However, there is scope for further study also about strategy of the decision making.

3.7 Singular points detection

In (Section 3.2), fingerprint images are divided simply based on the length. However, we are considering that the accuracy of classification should be improved by an ingenious scheme of the division. Figure 1 shows the common classes of fingerprint with core and delta points. The most popular approach for detecting fingerprint singularities is the method based on the Poincaré index. We describe the basic idea of the method in the rest of this subsection.

Since the Poincaré index is working on the direction changes, then the first step before calculating the Poincaré index is to extract the directional (orientation) image corresponding to the input fingerprint, Figure 12 shows the orientation filed for both core and delta point. To increase the accuracy of the orientation image, some enhancement techniques such as (Awad et al., 2007a) and (Awad et al., 2007b) can be implemented prior to the directional field estimation. We assume that $\theta(i,j)$ is pixel orientation of any directional image element pixel(i,j), where $0 \le \theta(i,j) \le \pi$. Let (i_k, j_k) for $0 \le k \le N-1$ is the element selected for calculating the Poincaré index of a point(i,j). Then, the Poincaré index is defined as:

$$Poincar\acute{e}(i,j) = \frac{1}{2\pi} \sum_{k=0}^{N-1} \Delta(k),$$ (1)

where

$$\Delta(k) = \begin{cases} \delta(k) & if\ \left|\delta(k)\right|\ <\ \pi\,/\,2 \\ \pi + \delta(k) & if\ \delta(k)\ \le -\,\pi\,/\,2 \\ \pi - \delta(k) & otherwise \end{cases}$$ (2)
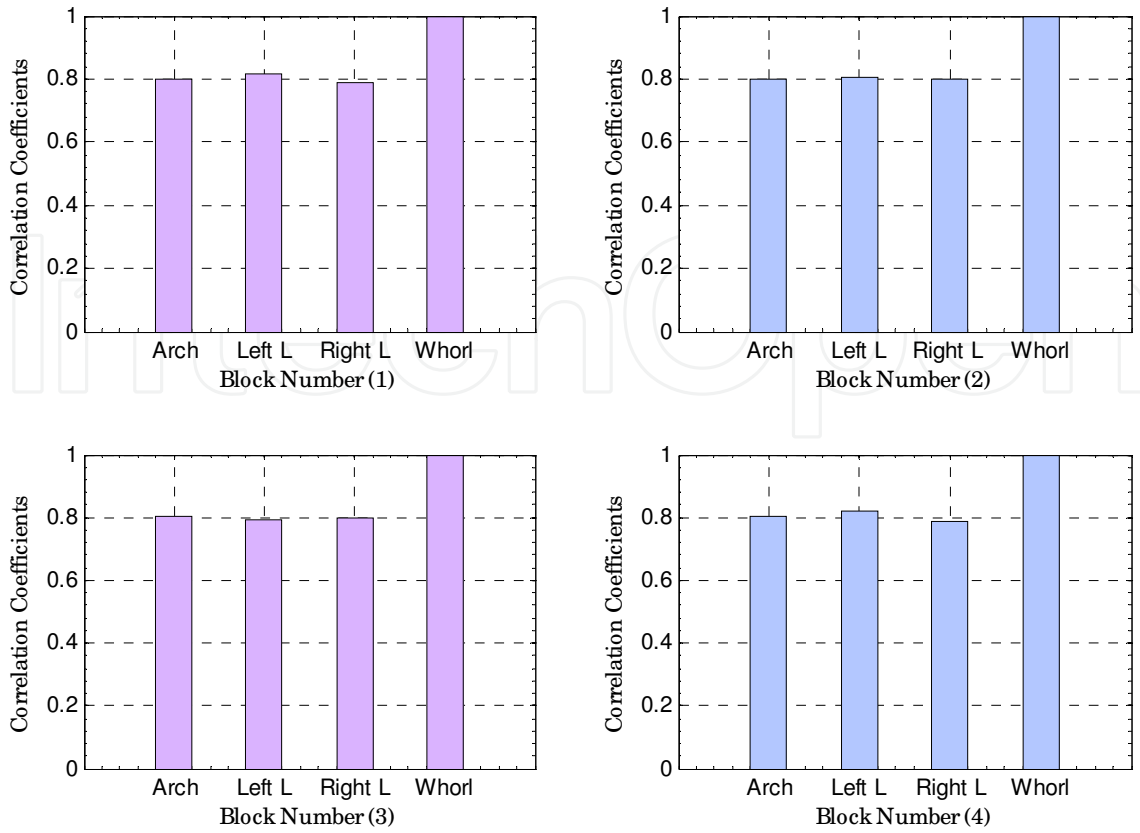
Fig. 10. Correlation results between input image patterns (Whorl) and other four classes
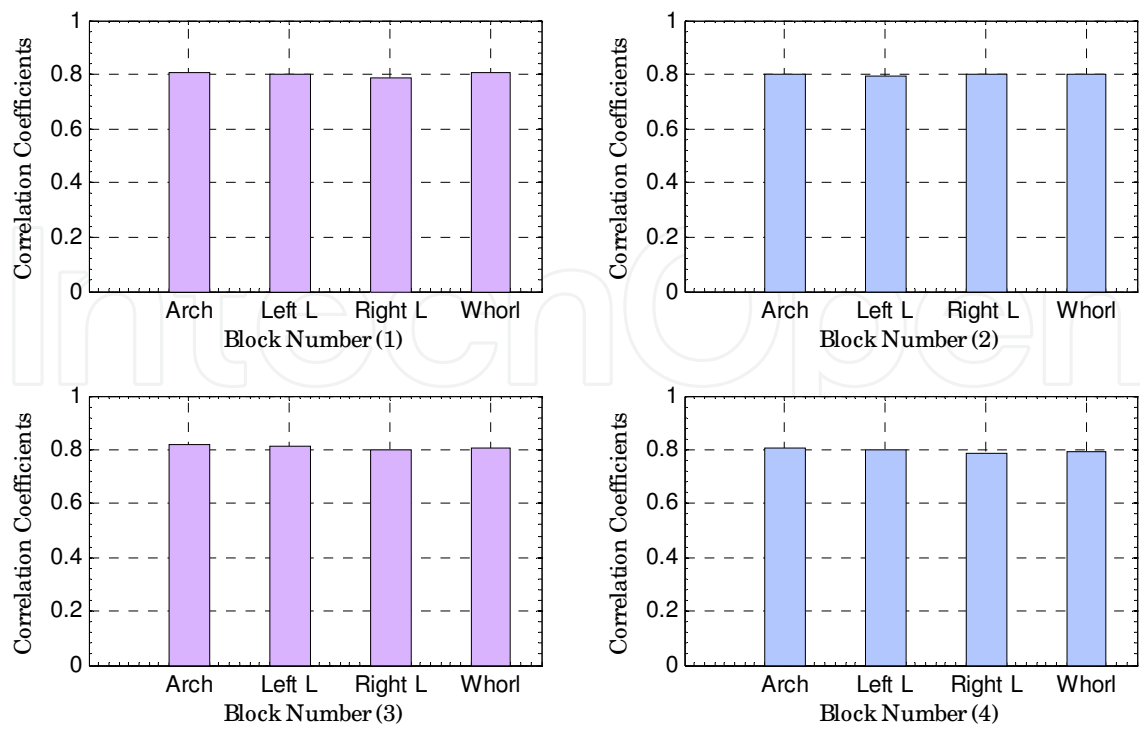

Fig. 11. Correlation results between input image patterns (Arch) and other four classes
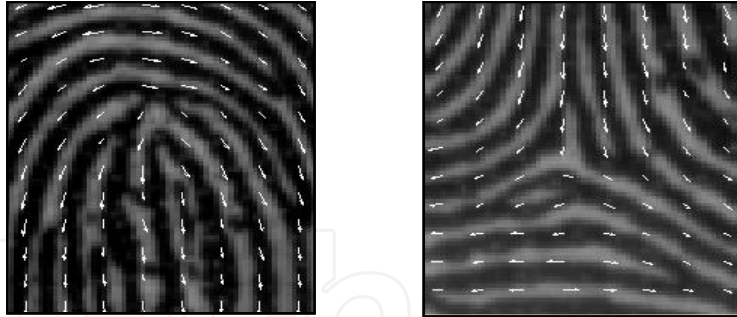
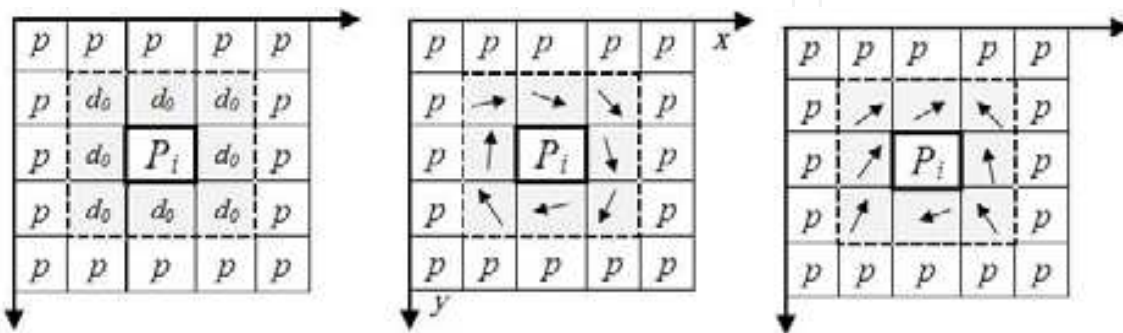Fig. 12. Estimated orientation field for core (left) and delta (right)

Fig. 13. Poincaré index representation: general Poincaré index calculation (left), Poincaré index = 1.0 (middle), Poincaré index = - 0.5 (right)

and

$$\delta(k) = \theta\big(x_{(k+1)\bmod(N)}, y_{(k+1)\bmod(N)}\big) - \theta\big(x_k, y_k\big) \qquad (3)$$

Then, the Poincaré index may have four kinds of values: 0 which means no singular point available in the area, 1/2 for a core point, -1/2 for a delta point, and 1 which means that the selected area may have two singular points. Figure 13 shows the differences between the most dominant values of Poincaré index.

4. Experimental results and evaluations

The proposed efficient fingerprint classification algorithm has been intensively evaluated through different conducted experiments. The overall consumed processing time has been optimized to enhance the overall algorithm performance. We have implemented two matching algorithms; pattern matching by image difference and by image correlation also. Optimization process tried to reduce the algorithm's response time to its minimum value.

4.1 Data sets

In general, standard databases are used for implementation and evaluation of fingerprint recognition or classification methods. We used NIST-4 for evaluating the accuracy of the classification by the proposed method. Actually, in a lot of related work the evaluation is operated on the whole or a part of NIST-4. As for the processing time, in addition to NIST-4, four subsets of Fingerprint Verification Competition 2004 (FVC2004) (Maltoni et al., 2009) were used (Figure 14 shows samples of fingerprint images in different subsets of FVC2004).
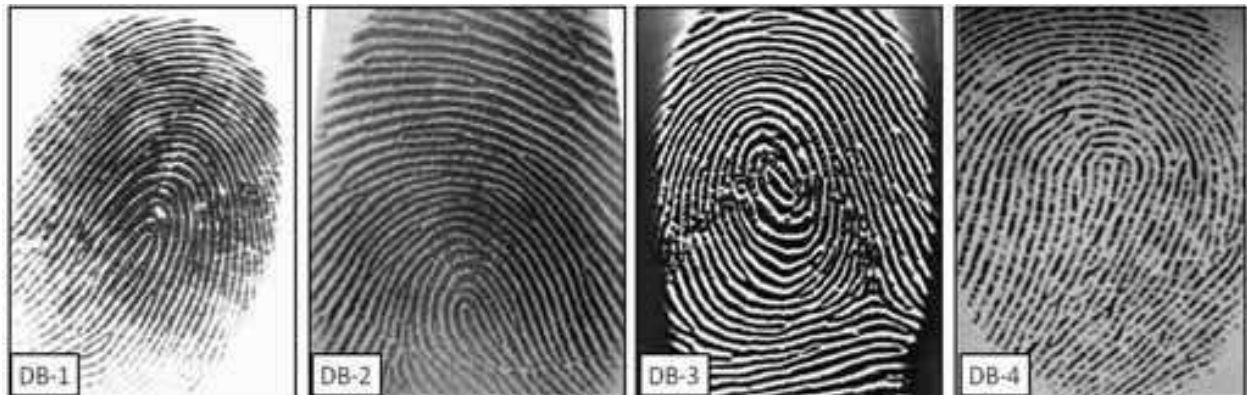
Fig. 14. Sample fingerprint images taken form FVC2004 available databases.

The selection criterion of the databases was interested to choose variety of fingerprints collected by different methods including optical, thermal sweeping sensors, and synthetic fingerprints. FVC2004 includes four sub databases: two categories generated by optical sensors, "V300" by CrossMatch and "U.are.U 4000" by Digital Persona respectively, the third one generated by thermal sensor "FingerChip FCD4B14CB" by Atmel, and the fourth is a synthetic by SFinGe proposed by (Cappelli, 2009).

4.2 Accuracy

The idea of confusion matrix is a common way to measure the performance of fingerprint classification algorithms. In a confusion matrix, a row and a column correspond to each actual class and each predicted class, respectively. Therefore, the diagonal elements are corresponding to the fingerprints that have been correctly classified. Table 1 is the confusion matrix resulted from applying the proposed method on NIST-4 database.

True Classes	Assigned Classes			
	A	**R**	**L**	**W**
Arch	**912**	37	36	5
R Loop	7	**672**	3	23
L Loop	10	6	**780**	33
Whorl	1	30	35	**731**

Table 1. The confusion matrix of implementing proposed method on NIST-4 database

Table 2 is the same result expressed in terms of the ratio, where "Fail Reject" and "Fail Accept" correspond to the ratios of the samples classified correctly in each row and column, respectively (therefore, both of them have the same value in "Total"). The result 6.9% of the error rate for the proposed method should be compared with the result 6% in (Park & Park, 2005) which uses FFT and NIST-4. The error rate is slightly worse compared to the existing method, however the calculation time is extremely small compared to the same existing method.

True Classes	Rates		
	Correct	Fail Reject	Fail Accept
Arch	92.1	7.9	1.9
R Loop	94.1	5.9	8.7
L Loop	95.3	4.7	9.8
Whorl	91.7	8.3	7.7
Total	93.1	6.9	-

Table 2. Classification results with False Acceptance and False Rejection rates of the proposed algorithm (%)

4.3 Processing time

Response time is the key issue in all fingerprint classification methods. We evaluated the processing time of the proposed method with respect to each step. The experiments were operated with Intel® Pentium 4 Core 2 Due™ processor (T9300, 2.5 GHz), 3 GB RAM, and Matlab® R2009b version. Table 3 represents the results of the processing time of the proposed method for one input fingerprint image. Each value is the average of the results for the fingerprint images in the databases. In the process of pattern matching, we evaluated the time of the difference-based method for the comparison with the correlation-based method. Note that the processes of "Division" and "FFT" are common in both methods. By the results, the total processing time of the proposed method is generally short in the sense of an application as an identification system. The correlation-based method is improving the computing time for the pattern matching process from the difference-based method.

	Division	FFT	**Pattern Matching**	Total
Correlation-based matching	0.0200	0.0229	0.0134	0.0552
Difference-based matching	0.0200	0.0229	0.0620	0.1056

Table 3. The processing time of the proposed method for each step (seconds)

4.4 Considerations

As we mentioned in (Subsection 3.6), we should consider a better scheme for the pattern matching and decision making. Does every block has the same weight during the matching process? Our experimental results proved that the answer is "No", and hence each block pattern may have different weight during the matching step. Furthermore, we go to optimize the matching processing by selecting number of blocks to be matched in each class. In other words, instead of matching the four blocks of each class, we match only the most dominant blocks in each class. The weight for each block and order are different for each fingerprint class, therefore the problem was how to select the most optimum blocks for each class. The problem has been solved empirically by testing each block individually and tried to assign it a weight related to the correlation matching results of the input image with its corresponding standard one. The test has been extended to check two by two blocks, and three by three blocks as well.

Matching two by two blocks, blocks number (1) and (2) of the input image with the corresponding blocks in the standard classes as an example, is considered as the summation of matching two individual blocks. It helped us to find the block that produces maximum correlation in the patterns matching process. As a case study, we input a Left Loop fingerprint, the classification algorithm detected that the input image is a Left loop correctly; however less block difference or high correlation score was our goal. Through the optimization process, we are trying to achieve as much smaller difference between blocks as possible, and hence we were seeking to get a less block difference between the input image patterns and the Left Loop standard class patterns. The first graph in Figure 15 represents the matching results come from using two blocks matching in the matching process and discarding the others. From that figure we see that the blocks (2) and (4) produce a minimum block difference that considered as a high matching score, where blocks (1) and (3) produce a low matching score. Therefore, we conclude that blocks (2) and (4) are the first optimum choice as a base blocks for matching the input image with the Left Loop class.
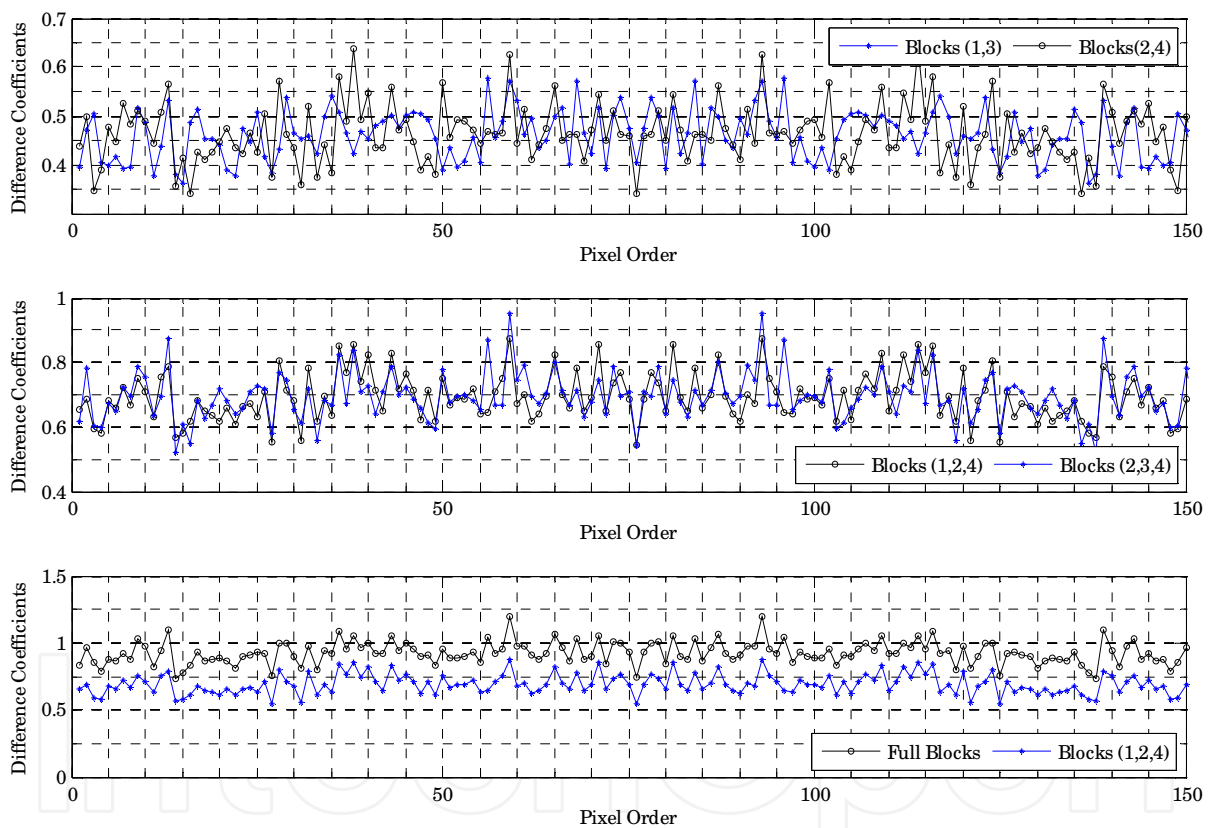

Fig. 15. Patterns matching optimization by two by two blocks (Upper), three by three blocks (Middle), and the amount of gained matching optimization (Bottom)

Due to the overlapping between classes, we found that two blocks are not sufficient for classification decision. Therefore, they are only used as a base blocks for determination of the maximum and minimum matching scores. To prevent overlapping between different fingerprint classes, we used three blocks from total patterns in matching process. The second graph in Figure 15 shows that the matching score produced from using blocks (1), (2), and (4) is much more than one produced by using blocks (2), (3), and (4). This figure leads us to conclude that blocks number (1), (2), and (4) are the optimum choice when

matching any input fingerprint image with the standard Left Loop class, and the third block may be discarded. The third graph in Figure 15 shows the amount of optimizations achieved by selecting three particular blocks in the matching process comparing to use the full patterns (four blocks). As we mentioned before, this experiments are operated as a case study and the order of blocks is different for each class. Therefore, we are going further to extend in the future the optimization process to include the remaining three classes to complete the general weight for our pattern matching.

5. Conclusions and future work

In this chapter, we proposed an efficient method which classifies fingerprints into the standard four classes. The basic idea of the proposed algorithm is dividing a fingerprint image into four sub-images before applying the standard FFT-based method of fingerprint classification. We have evaluated the proposed method in terms of the accuracy and the processing time by experiments with the standard databases NIST-4 and FVC2004. As the result, the proposed method achieves an extremely speed-up with a small classification losses compared to the simple techniques we have used. One of our future works is an improvement of the classification accuracy. For the improvement, we are considering that these is scope for further study about the division of images, the calculation of patterns, and the decision making. We mentioned about some ideas for the topics in Section 3.7, Section 3.4, and Section 4.4 respectively.

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Edited by Dr. Midori Albert

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