Partial Fingerprint Identification Through Correlation-based Approach

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Abstract: Partial fingerprints are likely to be fragmentary or low quality, which mandates the development of accurate fingerprint verification algorithms. Two fingerprints should be aligned properly, in order to measure the similarity between them. Moreover, the common fingerprint recognition methods (minutiae-based) only use the limited information that is available. This affects the reliability of the output of the fingerprint recognition system, especially when dealing with partial fingerprints. To overcome this drawback, in this research, a region-based fingerprint recognition method is proposed in which the fingerprints are compared in a pixel-wise manner by computing their correlation coefficient. Therefore, all the attributes of the fingerprint contribute in the matching decision. Such a technique is promising to accurately recognise a partial fingerprint as well as a full fingerprint compared to the minutiae-based fingerprint recognition methods which only concentrate on parts of the fingerprint. The proposed method is based on simple but effective metrics that has been defined to compute local similarities which is then combined into a global score and then used to make the match/non-match decision. Extensive experiments over FVC2002 data set has proven the superiority of our method compared to the other well-known techniques reported in literature.

1 INTRODUCTION

Fingerprint is an impression left by the friction ridges of a person's fingertip. It is one of the most well-known biometrics due to its uniqueness and consistency. Although the fingerprint uniqueness is accepted based on a manual inspection (by experts), its consistency has been proven by morphogenesis of friction ridge skin (Pankanti et al., 2002). Traditionally, fingerprint had been widely used and associated with criminal investigation, but now it has become more popular in other areas such as civil application (access control, financial security, etc.) as well (Vaidehi et al., 2010). Although a lot of effort has been put in the past 30 years to end up with a reliable automated system, we are still far from the good.

A number of factors which cause bottlenecks towards achieving desired system performance are: lack of reliable feature extraction algorithms, difficulty in accurately aligning the fingerprints and also in defining a reliable similarity measurement between fingerprints (Vaidehi et al., 2010). In addition, fingerprint individuality is empirically accepted, but fingerprint recognition is a difficult task, mainly due to the large intra-class (a.k.a. within-finger) variation and large inter-class (a.k.a. between-finger) similarity in fingerprints. Intra-class variation occurs when fingerprints are slightly different each time they are captured. So different impressions of the same finger are not identical; likewise, inter-class similarity refers to quite similar fingerprint impressions which are from different fingers (Maltoni et al., 2009). Intra-class variation is mainly caused due to partial overlap, non-linear distortion, sensor noise (Nandakumar and Jain, 2004; Parziale, 2008; Labati et al., 2014), and intentionally altering the fingerprint (Yoon et al., 2012). Non-linear distortion introduced during fingerprint sensing is certainly one of the most critical intra-class variability (Maltoni et al., 2009). It is produced by non-orthogonal pressure of the finger against the fingerprint scanner. The act of sensing maps the 3-dimensional shape of a finger onto the 2-dimensional surface of the sensor results in non-linear distortion in successive acquisitions of the same finger due to skin elasticity (Maltoni et al., 2009). Presence of noise in the fingerprint images could be due to the dirty fingers which also contribute to the intra-class variations (Nandakumar and Jain, 2004). Intentionally altering the fingerprint is usually done by criminals to hide their identity (Soweon et al., 2012).

Researchers proposed numerous fingerprint matching techniques which can be coarsely categorised into three major groups (Maltoni et al., 2009;

Donida Labati and Scotti, 2011): Minutiae-Based (i.e. (Kovacs-Vajna, 2000; Tico and Kuosmanen, 2003; Chen et al., 2005; Liu et al., 2005; Gao et al., 2011)), Non-Minutiae-Based (i.e. (Sha et al., 2003; Yang et al., 2007; Lumini and Nanni, 2006; Qader et al., 2007)), and Correlation-Based (i.e. (Lindoso et al., 2007; Karna et al., 2008)). Also, researchers proposed hybrid matchers which make use of more than one of the above-mentioned approaches (i.e. (Nandakumar and Jain, 2004; Ross et al., 2002; Benhammadi et al., 2007)). All the fingerprint matching methods can be roughly categorised into the mentioned groups based on the features they extract from the fingerprints. Fingerprint features can also be categorized into three major levels (Maltoni et al., 2009; Donida Labati and Scotti, 2011; Yager and Amin, 2004). Level-1 features (general patterns) are the macro information on the fingerprint such as ridge flow and ridge orientation. The level-1 features are mostly used to categorize the fingerprints into specified classes or pattern type (loop, arch, tented arch, etc.). Level-2 features are the minutiae, such as ridge bifurcations and endings. Level-3 features include all dimensional attributes of the ridge such as ridge width, shape, pores, incipient ridges, breaks, creases, scars, and other permanent details (Jain et al., 2007).

Regarding fingerprint features, it should be noted that some features could be highly-discriminative but are very sensitive to the quality of the images. Usually, minutiae features have these types of properties(Maltoni et al., 2009; Pankanti et al., 2002). Minutiae are defined as the points that a ridge ends or disjoints, therefore, minutiae extraction in low quality images will lead to detecting false minutiae due to the unclear ridges and valleys (Yager and Amin, 2004). Although extracting the minutiae from grey-scale image instead of skeleton image compensate for detecting false and spurious minutiae (Yager and Amin, 2004), designing a foolproof minutiae extractor to reliably detect these features is still an issue. Another disadvantage of Minutiae-based approaches is that they only use limited available information on the fingerprint. Pankati et al. claimed that extracted information in minutiae-based methods is limited, and algorithm developers should explore the use of non-minutiae based information as well (Pankanti et al., 2002). This problem becomes more serious when dealing with partial fingerprints since some of the remaining useful information is not used by minutiae-based methods. Typically, in a small area of a fingerprint, only 4-5 minutiae may exist and in that case, minutiae-based methods will not work satisfactorily due to limitation in providing fingerprint discriminative information (Maltoni et al., 2009).

On the other hand, correlation-based methods directly use the grey-level information from the fingerprint image (Nandakumar and Jain, 2004; Vaidehi et al., 2010; Lindoso et al., 2007). These methods take into account all dimensional attributes of a fingerprint which include micro characteristics such as minutiae, macro characteristics such as reference points, and also ridge shape, ridge thickness, etc. A grey-level fingerprint image contains richer and more discriminatory information than only the minutiae location. Furthermore, in correlation-based methods false/missed minutiae do not decrease the matching performance and even no hard decision needs to be made on the searching for minutiae pairs. Correlation-based methods are also capable of dealing with low quality images. Although Correlation-based methods have a higher reliability, their main drawback is their high computational cost (Nandakumar and Jain, 2004; Vaidehi et al., 2010; Lindoso et al., 2007). To overcome this issue different strategies have been proposed. One of these strategies is to use an appropriate region selection for comparison purposes (Lindoso et al., 2007). Moreover, the computation required to compute cross-correlation can also be achieved in Fourier domain (Douglas A., 2010; Lindoso et al., 2007). Finally, computing correlation of the local regions of the images can be performed in parallel.

To improve the performance of correlation algorithms, Karna et al. proposed a method based on normalized cross-correlation (Karna et al., 2008). Their method involves extracting the common region between two fingerprints (as one single region) and computing the correlation of the common region. The highest correlation coefficient value is considered as the degree of similarity between two fingerprints. The main limitation of this method is the alignment algorithm. This process is done manually by selecting points of interest from the template and query fingerprints. By so doing, the accuracy of aligning the fingerprints improves significantly. However, such an alignment strategy is not practical in AFIS (Automated Fingerprint Identification System) which requires processing large number of images. In addition, accurately aligning the fingerprints can significantly improve the system performance. Another drawback of this method relates to dealing with non-linear distortion. If the similarity measurement is not applied locally, the matching result will suffer from non-linear deformation.

Nandakumar and Jain proposed a hybrid method of minutiae and correlation (Nandakumar and Jain, 2004). Their method is based on computing the correlation of small region around minutiae points and takes the average of the correlation values as the final similarity degree of two fingerprints. Although their approach can sufficiently deal with non-linear distortion, it suffers from being dependent on the minutiae points. The two main problems of minutiae-based methods (working on limited information and detecting spurious/false minutiae) also prevents this method from providing better result. Nandakumar and Jain also stated that *"the grey-level information of the pixels around the minutiae point contains richer information about the local region than attributes of the minutiae points"*.

2 PROPOSED METHOD

The proposed correlation-based method consists of the following major steps: fingerprint alignment, common region extraction, and computing the degree of similarity. As in other methods, the fingerprints are enhanced and segmented as the preliminary steps of the proposed method.

In a pixel-wise comparison of the images, the *corresponding regions in two images* need to be compared. In order to compute the correlation of the same regions, the translation difference can be taken care of by applying the sliding window technique. Therefore the images only need to be rotationally aligned. Rotational alignment of two fingerprints refers to rotating the fingerprints so they become as identical as possible in the orientation. In partial prints, there may be a small overlap between the two fingerprints, hence a suitable strategy needs to be performed to align them. In section 2.1, the alignment method is discussed which also addresses the alignment issues in Karna et al.'s method (Karna et al., 2008).

After alignment step, in order to extract the common regions between two fingerprints, first they are decomposed into smaller regions. Then, by projecting the common singular points of the two fingerprints, the regions which are located at the same location with respect to these points, are identified as the common regions (section 2.2).

After identifying the common regions between the two images, similarity of two fingerprints is measured (section 2.3). As discussed, there may be a small overlap between two partial fingerprints. Thus, in order to utilise all the available information, correlation of the overlapped regions is computed. Correlation of each small regions in query image is computed with respect to the corresponding one in registered image. Dividing the fingerprints into smaller regions and computing the similarity of the fingerprints locally will minimize the effect of the non-linear distortion (depending on choosing a reasonable size of the regions). A large size region cannot properly handle the non-linear deformation. On the contrary, correlation of a small size regions are more affected by the small distorted parts of that region (compared to large size regions). Apart from these points, region size should be small enough to cover most of the fingerprint information close to the borders. By computing the local similarities, all the attributes contained in the fingerprint is utilised. To obtain the final similarity score of two fingerprints (global similarity), the local similarities are averaged. The Block diagram of the proposed method is presented in Figure 1. All the steps is described in detail in the following subsections.

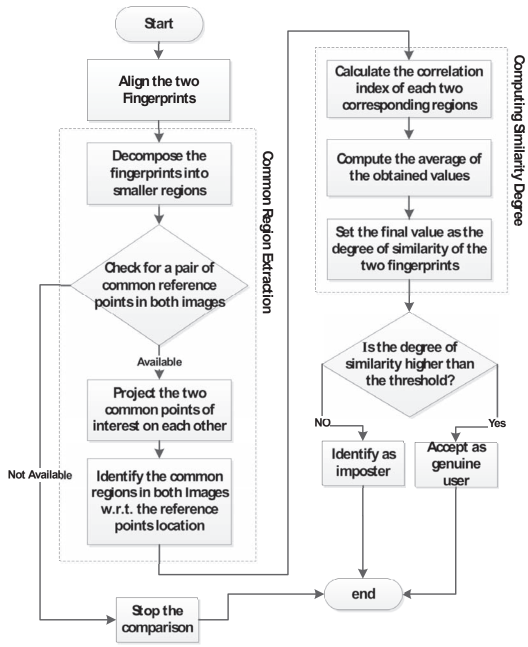

Figure 1: Block diagram of the proposed matching method.

2.1 Fingerprint Alignment

One of the intra-class variations is the rotation difference in two fingerprints. In our proposed method a pixel to pixel comparison of both images is computed, therefore even a slight rotation difference between the two images, could result in an inaccurate matching decision. In other words, an accurate alignment lead to reducing false rejection of the genuine users in the system.

The previously developed fingerprint alignment methods, including minutia-based and non-minutia feature based ones, are not completely suitable for partial fingerprints. One issue of applying these methods to partial prints is that the required features could be very few on the fragments. Accordingly, they will either lead to incorrect alignment or not being applicable for partial fingerprints (Zhao et al., 2010). For instance, Khalili et al. have investigated on using fingerprint reference points to rotationally align the fingerprints (Khalil et al., 2009). However, it is likely that reference points are not available in partial fingerprints. Therefore, it is critical to align the partial fingerprints only based on the available features.

This issue in partial fingerprint alignment can be reasonably overcome by using the remaining information in the fragment. In addition, since the shape of the partial fingerprint is not fixed, the fingerprints must be aligned adaptively to the partial print shape. In alignment step, a new approach to align the fingerprints based on the correlation of fingerprints (using the micro features, refer to section 2.1.1) and their singular points (using macro features, refer to section 2.1.2) is applied. The resulting algorithm is not only simple and intuitive, but is also robust and accurate.

2.1.1 Alignment based on Fingerprint Micro Features

As discussed in section 1, the region-based comparison include much richer information than minutiae-features for matching while being more reliable with respect to the image quality. The same discussion is applicable for the features to use to align the fingerprints.

The process starts with cropping a region from the query fingerprint. The size of the cropped region can vary depending on the size of the valid fingerprint regions. In addition to the size of the region, it can be cropped from different part of the query fingerprint. These two properties make this strategy suitable for partial fingerprints alignment. For each of the cropped regions, the correlation of the cropped region and the registered fingerprint is computed for different rotation angles. The rotation angle which gives the highest correlation value, is used to rotationally align the two fingerprints.

By aligning the fingerprints in this way, partial fingerprints can be aligned even though there is no singular point available. In addition, the fingerprints are accurately aligned since the finger skin elasticity is handled and the effect of distorted regions on the fingerprint is ignored, due to the point that different regions (with different sizes) can be cropped from the query fingerprint. The result of aligning by this strategy is shown in Figure 2. Although this strategy is accurate, it is not efficient in terms of computation cost. Each cropped region is rotated by -35 to +35 degree till the rotation difference is found. In order to increase the efficiency, the singular points position (if available) on the fingerprint is used as the second strategy.

Figure 2: A pair of impression of the same finger being aligned based on computing the correlation of their ridge structure.

2.1.2 Alignment based on Fingerprint Macro Features

The fingerprints are generally 2-dimensional images which could be rotationally aligned if two identical points can be located in both images. Singular points (if available) could be used to align the fingerprints *efficiently* based on this theory. In this study, the locations of singular points are detected based on the method proposed by Wang et al. (Wang et al., 2011).

The ideal situation in intra-class cases is that the location of any singular point in one image should be identical to the location of corresponding singular point in the other image. For instance, the difference in the Euclidean distance between core and delta point in two intra-class fingerprints "*A*", and "*B*", should be very small. If so, the idea of using the singular point location for alignment is promising. Considering the four types of singular points in a fingerprint (upside core, downside core, right delta, and left delta), there are six combinations of them. Figure 3 shows the plot of subtracting the Euclidean distance between singular points of intra-class and inter-class fingerprints. The experiment is conducted on the public data set FVC2002_DB1. As shown, generally the subtraction between the Euclidean distance of the two pairs of singular points locations in intra cases is much lower than those in inter-cases (desired). On the other hand, in some intra-cases, this value is more than the ones in inter-cases due to the intra-class variation (undesired). In this case, aligning the fingerprints based on the position of reference points will not be accurate, but it still could be used for a *coarse alignment* (to take advantage of the efficiency of this strategy).

Assume two pairs of the same reference points exist in both fingerprints. To align them based on their position and angle with respect to x-axis, the query image is rotated till the gradient of the two common reference points are identical.If $C_R(x_1, y_1)$ and $D_R(x_2, y_2)$ are core and delta points respectively in registered fingerprint, likewise $C_Q(x'_1, y'_1)$ and $D_Q(x'_2, y'_2)$ are core and delta points respectively

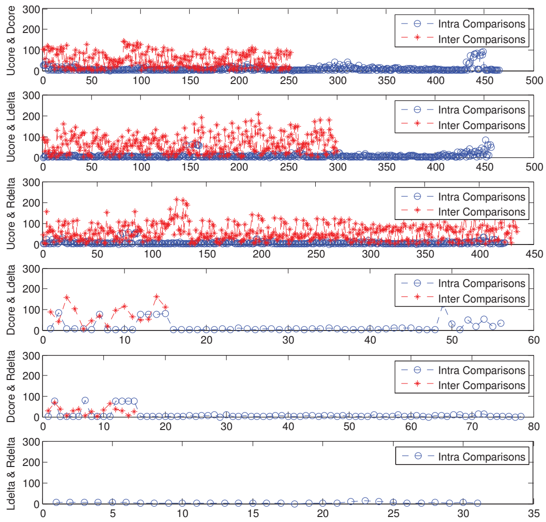

Figure 3: y-axis indicates the difference between the Euclidean distance between each pair of singular points in intra and inter class fingerprints (in pixels), x-axis indicates a comparison in inter/intra. Ucore = upside core, Dcore = downside core, Ldelta = left delta, and Rdelta = right delta.

in query fingerprint, the angle between (C_R, D_R), and (C_Q, D_Q), (θ_1 and θ_2 respectively) is computed as follows:

$$\theta_1 = tan^{-1}(\frac{y_2 - y_1}{x_2 - x_1}), \qquad \theta_2 = tan^{-1}(\frac{y_2' - y_1'}{x_2' - x_1'}) \quad (1)$$

$$angle = \theta_2 - \theta_1 \quad (2)$$

Eq. 2 indicates the angle that query fingerprint must be rotated in order to be aligned with the registered fingerprint.

Figure 4 illustrates an example of aligning the fingerprints based on the above process. Figures 4(a) and 4(b) show the registered and query fingerprints respectively, which are different impressions of the same finger. To align the query fingerprint with the registered one, the query fingerprint should be rotated clockwise. The red and green circles depict the location of up-core and delta respectively on both of the fingerprints. According to the position of the core and delta points on registered image and by using Eq. 1, $\theta_1 = +111°$ and likewise $\theta_2 = +116°$. Then the angle (Eq. 2) is $-5°$ which means the query image should be rotated by 5° (clockwise) to be aligned with registered image (Figure 4(c)). In this case, the singular point detection method correctly identified the position of the singularity, but due to the intra-class variation, core and delta points changed their position in two different impressions. In these cases using the position of the singular points will not result in an accurate alignment. However, the fingerprints were coarsely aligned which significantly improves the alignment efficiency in total.

(a) Registered image. (b) Query image.

$$\theta_1 = +111, \theta_2 = +116, angle = \theta_1 - \theta_2 = -5$$

(c) Query image rotated by $-5°$ (d) Query image rotated by $-35°$

Figure 4: Aligning the query fingerprint (b) with respect to registered fingerprint (a), in (c) only fist strategy used to align the fingerprints, in (d) alignment is done by combining first and second strategy

2.1.3 Alignment by Hybrid of Micro and Macro Features

Considering these two strategies, combing the two alignment strategies results in taking advantage of accurately aligning by using micro features and efficiently aligning by using macro features. Figure 5 shows the ROC plot of the discussed alignment method. Each curve shows the False Reject Rate (FRR) versus False Accept Rate (FAR) (refer to (Cappelli et al., 2006) for FAR and FRR explanation) for different degree of rotation used in second strategy. The red curve shows the system performance when rotation angle is set to zero which is equivalent to only applying the second alignment strategy (coarse alignment). As depicted, by increasing the rotation angle (in first strategy), the Equal Error Rate, EER (where FAR = FRR, (Cappelli et al., 2006)) decreases.

Furthermore, the ROC curves associated with the rotation angles of 0 and 5 shows significantly higher FAR and FRR compared to the ROC curves associated with the rotation angles $10, 15, 25, 35$, and 45. As mentioned in (Maio et al., 2002), the maximum rotation difference between any two samples in this dataset is a maximum of 35°. This will lead us to the

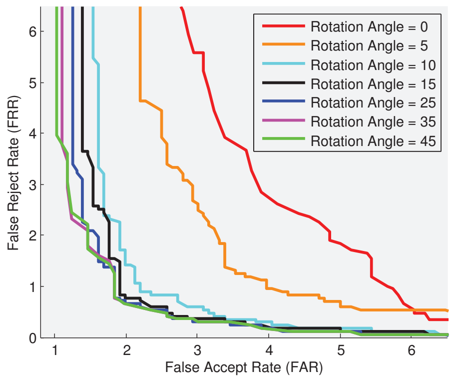

Figure 5: ROC of the proposed method by using different rotation angles in second alignment strategy.

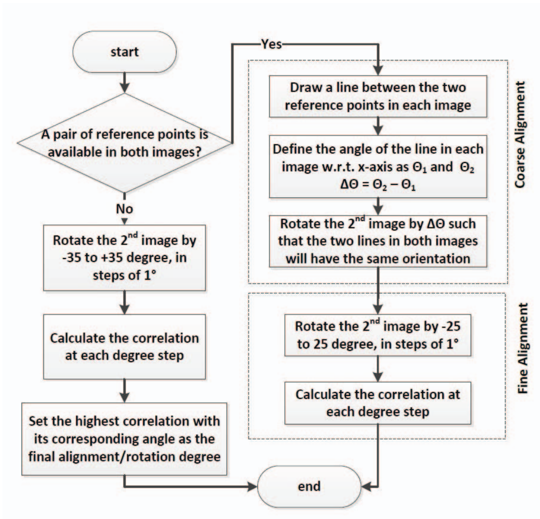

Figure 6: Block diagram of the proposed alignment method.

optimal rotation degree that can result in lowest FAR and FRR. Considering that *at this point fingerprints are coarsely aligned*, there is not much difference between the curves for rotation angles of 15, 25, 35, and 45. This can be concluded that the rotation angle 15 is the optimal degree of rotation needed for this dataset. Block diagram of the proposed method for alignment is presented in Figure 6.

There is one more step needs to be performed after fingerprints are aligned to make sure the same regions are compared between two fingerprints. In next section, how the common regions between two fingerprints are extracted is discussed.

2.2 Common Region Extraction

Local matching techniques are proposed to overcome the problems such as lack of robustness with respect to the non-linear distortion in global matching techniques (Cappelli et al., 2010). In order to locally match the fingerprints, they are decomposed into smaller regions. The main reasons that the local matching techniques perform better than the global ones are:

- Their capability in handling the non-linear distortion of the fingerprints (refer to section 1 for non-linear distortion definition).
- The effect of the distorted regions on the final similarity degree is reduced by dividing the images into smaller regions (refer to section 2.3).

With regard to the size of the smaller regions, in computing the correlation of two images, there is a trade-off between size of the region and sensitivity to distortion. If the selected region size is too small it will not capture enough image information and will be too sensitive to the distortion. This may result in miscalculating the correlation of that region. On the other hand, if the region size is too large, it becomes less sensitive to the distortion (desired) but also less sensitive to the actual variations of the fingerprints (not desired). Considering the resolution of the fingerprints in the dataset, it is observed that the minimum region size required for any feature to be extracted is 50×50 pixels (refer to section 3). Moreover, this size is also used to extract the common regions between the two fingerprints.

In order to extract the common regions, at least one common reference point needs to be located on both fingerprint. The query fingerprint is projected on to the registered fingerprint by aligning their common reference points. Subsequently, the overlapping regions are identified to be the common regions between the two fingerprints.

2.3 Computing Degree of Similarity

Due to the small overlap in partial fingerprint matching, a similarity measure that can reflect all the distinguishing characteristic of a fingerprint is essential. As discussed in section 1, correlation coefficient of two fingerprints reflects all the available features. Therefore, the similarity of two fingerprints is computed in terms of their correlation coefficient. In addition, as discussed in section 1, the fingerprints could suffer from the distortion. The distortion on a fingerprint may not be uniformly distributed and different regions may have different image quality levels. Thus, computing the similarity of the fingerprints locally (small regions extracted in section 2.2) reduces the effect of the distorted regions. In next section, the details of computing the local similarities and why it tolerates the effect of distorted regions on similarity degree of the fingerprints is discussed followed by computing the global (final) similarity degree through consolidating the local similarities for comparison.

2.3.1 Local and Global Degree of Similarity

Conventionally, in correlation-based methods, the whole fingerprints were considered as one big *single-region*. Accordingly, the degree of similarity was computed based upon the correlation of the two single-regions. In order to lower the effect of distorted regions on fingerprints, the similarity of two fingerprints is computed locally (in small-region level) and then the average value of local similarities is considered as the final similarity score between the two fingerprints. Computing the similarities of each pair of small-regions individually and then averaging them to obtain the global similarity is a robust and reliable technique for fingerprint matching. The reason is that the final similarity degree could be computed by giving the same contribution to each of the local similarities and by so doing, the distorted regions is taken into account as one value (local similarity) and it is not affecting the similarity of other regions. Hence, in our method, first the Normalized Cross Correlation (NCC) of each two corresponding regions is computed as local similarities. The NCC of 2-dimensional images f and t is calculated as (aka Pearson's r correlation) (Yoo and Han, 2009):

$$NCC = \frac{1}{n}\sum_{x,y}\frac{(f(x,y)-\bar{f})(t(x,y)-\bar{t})}{\sigma_f\sigma_t}, \qquad (3)$$

where $\bar{f}$ and $\bar{t}$ are the mean and σ_f and σ_t are the standard deviation of the images f and t respectively and n is the number of pixels of the images.

Common regions between registered and query fingerprint are not always detected completely accurately due to the following two reasons. First: as mentioned in section 2.2, extracting common regions is based on the position of the common reference point. However, the reference points are not always precisely located. Therefore, the detected common regions based on the location of these points are also not always precisely located. Second: even if the reference points are located precisely, it is still very challenging to precisely locate the corresponding regions due to the intra-class variation and non-linear distortion. Therefore, the corresponding region on registered fingerprint needs to be chosen greater than the one in query image to compensate for the small errors in computing the exact location of the corresponding regions.

After the local similarities are computed, a particular value (as global score) needs to be obtained from the local similarities to indicate their overall degree of similarity (Cappelli et al., 2010). In our method, to obtain a degree of similarity between the two fingerprints (global score/similarity), the local similarities are averaged. It should be mentioned that computing the similarity of fingerprints in such a way reasonably handles the intra-class variation and inter-class similarity, however to get the best out of this method it still could be improved. One promising technique to add to the current method is measuring the quality of small regions and compute the local similarities only based on the good quality regions. This is part of our future wok which is explained more in section 4.

3 EXPERIMENTAL RESULT

An experiment is performed on DB1 of the public dataset FVC 2002 (Fingerprint Verification Competition) which contains 800 fingerprints from 100 different fingers (8 impressions per finger). As discussed in (Maio et al., 2002), for the data set FVC2002 DB1, the participants that volunteered to provide their fingerprints, were asked to intentionally change the orientation of their finger on the scanner when scanning different impressions (to make the different impressions vary rotationally). In addition, no effort was made to control the image quality and the sensor plates were not systematically cleaned and high quality images were removed from the dataset. Therefore, due to rotation and displacement of the finger when scanning, there is often only a partial overlap between different impressions of the same finger and hence, the images in the data set include low quality and partial fingerprints as well. As discussed in previous sections, no matter how partial the fingerprints are, they can be aligned, their common regions are extracted (as long as a common reference point is available), and their local and global similarities are computed. The proposed method is designed in such a way to fulfil the requirements of partial fingerprint matching as well as complete fingerprint matching.

Regarding the time cost of the proposed method, the matching process of two fingerprints takes about 1.5 minutes on a computer with 3.1 GHz CPU and 8 GB RAM. This time has a direct relationship with how partial a fingerprint is. The smaller the available valid regions are, the less time is required for matching process. Considering the size of the dataset, and the time cost of the proposed method, the comparisons were conducted on Monash University High Performance Computing Cluster.

Table 1 indicates the result of the proposed method on the FVC2002 data set (in terms of the met-

Table 2: Comparison of the proposed method with previous works in terms of EER(%) value on dataset FVC2002_DB1. The methods are roughly categorised into the three major groups of fingerprint approaches.

Category	Method	EER (%)
Minutiae	(Kovacs-Vajna, 2000)	4.3
	(Tico and Kuosmanen, 2003)	4.0
	(Chen et al., 2005)	4.6
	(Liu et al., 2005)	4.3
	(Gao et al., 2011)	3.5
Non-Minutaie	(Sha et al., 2003)	6.23
	(Yang et al., 2007)	3.64
	(Lumini and Nanni, 2006)	4.2
	(Qader et al., 2007)	7.13
Hybrid	(Benhammadi et al., 2007)	4.2
Single-Region	Conventional Method	7.1
Multiple-Region with region size: 50×50 pixels	Proposed Method	2.32

Table 1: The result of the proposed method in terms of EER (%) value on data set FVC_2002_DB1 by using different region size. The last column shows the threshold used to compute the EER.

Proposed Correlation-Based Method	EER (%)
Region Size = 100×100	4.37
Region Size = 90×90	3.27
Region Size = 80×80	2.92
Region Size = 70×70	2.58
Region Size = 60×60	2.35
Region Size = 50×50	2.32
Region Size = 40×40	2.40
Region Size = 30×30	2.48
Region Size = 20×20	2.79

ric Equal Error Rate, EER) where the fingerprints are decomposed to different region sizes in order to extract their common regions (section 2.2) and compute their similarity degree (section 2.3). As shown in this table, the *smaller the region size* is, the *more accurate* the system performance will be. It is empirically observed that the region size 50×50 is the optimum region size for this data set which is required to extract the available features in a fingerprint.

Table 2 illustrates the comparison of our method with previous works in terms of EER value. Our method produces the lowest EER of 2.32%. The main advantage of our method compared to the others is using all the available dimensional attributes of the fingerprint. That includes all the three level of features mentioned in section 1. In addition, many methods are proposed to extract the level-3 features of the fingerprint, but extracting the level-3 features such as pores from low resolution fingerprints is very challenging. On the other hand, our proposed method is able to take into account all the possible distinguishing information in the fingerprint, regardless of the image quality (not very dependent on few particular features).

To demonstrate the effectiveness of the proposed multiple-region based method, its result is compared with the single-region correlation (conventional correlation-based method). It was observed that averaging method improved the EER from 7.1% to 2.32 % with respect to the single-region correlation-based. This improvement is achieved due to the robustness of the proposed method in reasonably handling the non-linear distortion and lowering the effect of the distorted regions in the fingerprint images (refer to section 2.3 for details).

Cappelli et al. (Cappelli et al., 2010) stated that local minutiae matching techniques can be categorised into two family of *nearest neighbour-based* and *fixed radius-based*. Methods in nearest neighbour-based family (i.e. Gao et al.'s approach (Gao et al., 2011)) the *k* closest minutiae to a central minutiae are defined as the neighbours of the central one. These methods lead to a fixed-length descriptor that can be matched efficiently. Gao et al.'s method uses the nearest neighbour structure information to match the points which carries on global matching at the end. In addition, their method is invariant to rotation and translation which saves the effort needed to align the fingerprints.These are the main advantages of Gao et al.'s method which lead to the lowest EER in the table. On the other hand, further to the issues which Gao et al.'s method suffer from as a minutiae-based method (refer to section 1), their method is not able to consider the effect of non-linear distortion of fingerprint images. Also nearest neighbour-based methods are not very tolerant to missing and spurious minutiae as the objective in these methods is to find the *k* nearest minutiae points (Cappelli et al., 2010).

The best EER in non-minutiae category belongs to Yang et. al's (Yang et al., 2007) method. Yang et al.'s method is based on extracting invariant moments of the fingerprint. Invariant moments were first introduced by Hu (Ming-Kuei, 1962). Hu proved that his seven moments are invariant to RTS (rotation, translation, and scaling). These moments are widely used in pattern recognition. Yang et al. applied these moments in fingerprint matching. Although their method is invariant to RTS and is efficient in terms of computation, there are some limitations in their work. First problem is that they only make use of a small region of the fingerprint (around reference points) while the rest of the information remains unused. Second problem is that they used 75% of the dataset as training set, while all the dataset (including the training set) is used to evaluate their method (as test set). This significantly affects the performance of the system and lead to a lower EER compared to evaluating the system only on the test set.

4 CONCLUSION AND FUTURE WORK

In this paper, we proposed a new method to measure the similarity of the fingerprints based on correlation coefficient. The method is composed of three main steps: alignment, common region extraction, and computing the final degree of similarity. Regarding to the alignment, pros and cons of the two strategies discussed which lead to combining them together to end up with an accurate and efficient method. The common region extraction was obtained by dividing the images into smaller regions, and projecting them on each other with respect to their common reference points. The most important step that had a great effect on the EER, is measuring the degree of similarity between two fingerprints. Based on the correlation coefficient, a new methodology to improve the accuracy for reliable fingerprint recognition proposed with especial interest in partial fingerprints. To this end, computing the similarity degree was decomposed in two sub-steps. First, the two images were divided into smaller regions, and the correlation of the corresponding regions were computed (as local similarities). Thereafter, the mean value of the local similarities is calculated as the final degree of similarity. It was observed that computing local similarities and assigning their average as a final degree of similarity result in a higher recognition accuracy compared to its conventional single region calculation. As a consequence, the EER is enhanced by almost 3 times as compared to a single region correlation. This proves the effectiveness of including an appropriate averaging method in the recognition algorithm. Regarding other available studies, our result gives a 33.7% improvement over the previous works.

Regarding our future work, as mentioned in section 2.3, measuring the quality of the small regions and processing only the good quality ones is a promising step to add to the current method. By so doing, inter and intra cases are more discriminated. Two intra fingerprints are supposed to have a high correlation in every region and vice versa for inter fingerprints. However, one of the main reasons that intra fingerprints result in low similarity is that some parts of the fingerprint are distorted. Therefore, identifying the low quality regions and ignoring the correlation of those regions will help to increase the similarity of intra cases. On the other hand, this strategy will not significantly affect the similarity degree of inter-cases. The low similarity in inter cases is the result of the difference between the ridges and valleys structure of the two fingerprints and not only the quality. In other words, the similarity on inter-cases will increase but not as much as it does for intra-cases.

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