2D Contactless Fingerprint Identification System for Sensor Interoperability

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Abstract

Automatic fingerprint identification system, AFIS is essential and most reliable biometric technology and the improvements in the performance are always necessary important for the security process of national and worldwide applications. With the combination of the emergence of various sensor technologies and the problems of the Big Data era, the requirement of health care mechanisms in today's world lead to the researchers emphasizing the contactless security mechanism and sensor interoperability problems. The transmission of a large amount of image processing data and the requirement of the high volume of storage for image processing face many troubles in cyber applications. Therefore, this paper proposes a framework for contactless fingerprint for 2D images and the recognition is intended to the cross-matching to solve the different sensors problems. In addition, the proposed system reduces the complexity by proposing effective features to increase the performance by using a machine learning classifier. The experiments are performed by using the public dataset of the PolyU database and the results are compared with the previous systems and achieve acceptable outcomes.

Keywords: AFIS, Big Data, Biometric Technology, Contactless Fingerprint, 2D images, PolyU Database, Sensor Interoperability Problems, Machine Learning

1. Introduction

The fingerprint is one of the most popular security controls in biometrics modality as the patterns of finger skin are unique to humans. It serves as an essential basis of forensic science and has attracted to employ in a wide range of national ID applications such as e-governance, e-business, and law-enforcement [1, 2]. Fingerprint recognition is the process of classifying or authorizing the individual identity by comparing the input finger and trained fingerprints. It is one of the most popular researched topics in recent age and reliable biometric mechanisms for today's world applications at the identifications and authentication process [3].

Fingerprint Recognition can be categorized into contact-based and contactless depend on the type of fingers used in the recognition process, especially rely on the image acquisition methods. The traditional contact-based methods need the users to roll or press their fingers on the hard surfaces such as paper, glass, polymer, or silicon. The contactless methods need not be contacted between the users' fingers and sensors. However, with such contact-based fingerprint recognition, the sensing methods suffer from various limitations and the requirements of available state-of-the-art matching algorithms. The sensing methods in contactless can acquire more ground truth information of fingers and can provide a more user-friendly mechanism, can improve more accuracy performance, can improve hygiene [1] that prevents health care problems like COVID 19. The comparison between touch-based and touchless 2D fingerprint recognition are listed in Table 1.

The contactless fingerprint recognition is more reliable and can provide highly promising and it is an essential component in AFIS, an automatic fingerprint identification system.

Table 1. Comparison between contact-based and contactless fingerprint recognition

Description	Contact-based	Contactless
Recognition Accuracy	High	High
Security on Sensors device	High	Very Low
Skin Deformation	High	NIL
Sensor surface noise	High	Very Low
Identification of spoof	Low	Medium
Sensor Cost	Low	High
Bulk/size	Compact	Medium/ Large

However, there may be many challenging in achieving high accuracy performance of contactless fingerprint recognition due to many characteristics of the above problems [4]. Therefore, the contactless fingerprint recognition mechanism is attracted by the attention of researchers, and various types of previous works have been proposed. The Contactless fingerprint recognition can be categorized into 2D and 3D based recognition methods rely on the dataset and the methods are different according to these types. Low-cost single-camera usually used to acquire the image of a finger for

2D methods and is suitable for most of the applications in some situations rather than 3D [5].

Although, there is a lot of normal contact-based fingerprint system and contactless systems, the number of the cross-matching system for sensor interoperability between lack of contact and contact-based is very little. Moreover, the requirement of the security process in the contactless biometric paradigm is emerging and the requirement of a large volume of data storage is increasing in most of today's world applications. Therefore, this paper proposed a 2D contactless fingerprint recognition system with the cross-matching capability for different sensors types by managing to store the small volume of image data. The rest of the paper is organized as follows; Section 2 discusses the previous related works for contactless fingerprint systems. Section 3 proposes the contactless system. Section 4 presents the experimental evolution and Section 5 completes the proposed work with little conclusion.

2. Related Works

There are a lot of works for the fingerprint recognition system matching single dataset or across datasets using feature extraction or without features and employing different types of machine learning strategies and matching of vision processing methods.

The authors of [2] proposed a mechanism to match contactless and contact-based fingerprints for the Biometric identification system. Their mechanism does not depend on the minute extraction method. They developed an RTPS, robust thin-plate spline to correct deformations of the sensors' problems and used the deformation correction model called DCM for fingerprint matching. They used PolyU sets of Contactless and Contact-based Fingerprint image Database for experiments and achieve 94.11% for the contact-based dataset and 66.67% for cross-matching datasets but they don't describe the performance of contactless dataset.

The group in [5] proposed contactless fingerprint matching mechanisms using a feature extraction method for the 2D and 3D contactless dataset. They segmented the touchless finger from the background and enhanced to increase the ridges and valleys contrast. Then the 36-dimensional minutiae features vectors are extracted after removing false correspondences. Then matching algorithm for minutiae is used and correspondent ridge matching is performed. Although they described they achieve the performance, the statistics are not described.

The authors have proposed a framework to match between contactless and contact-based fingerprints using Convolutional neural networks (CNN) in [6]. Their framework firstly extracts minutiae and ridge map from fingerprints and train multi-Siamese CNN. The train network is used in combination with loss function calculate on the distance to produce fingerprint feature vectors. The result for the cross-matching is achieved 64.59% for PolyU set of Contactless and Contact-based Fingerprint image Database and they also don't describe the contactless.

The researchers in [7] analyzed the fingerprints classification using image processing and ML, machine learning methods. Their goal is to reduce the complexity of fingerprint recognition in large datasets. They recommended that although the time of the pre-processing stage may be increased due to computation vision algorithms, it can improve the quality of the input images. The use of feature extraction techniques and machine learning methods can be highly effective and produce fast and accurate performance. They compared the experimental results of the state-of-the-art algorithms against the contact-based BD-HLG database, FVC database, and NIST-DB4 database and Random Forest is the best between them and achieves 97.86%.

The investigators in [3] proposed a Fingerprint Recognition system using a supervised Deep Learning machine learning method. They extract patterns point features, minutiae point features, and pore and contours features from the fingerprints using CNN. Then 22 layers of CNN including 5 convolutional are used for feature classification. They highly recommended that a robust CNN-based approach for minutiae features points can give great benefit to forensic applications.

To the best of our knowledge, the contactless fingerprint recognition process is more suitable for today technologies era rather than normal traditional touch-based systems and the effective feature extraction method can improve the performance of the fingerprint recognition system using machine learning methods.

3. Proposed System

The proposed system consists of four main parts:

1. Main reference points detection
2. Minutiae extraction
3. Feature extraction
4. Classification

3.1. Main Reference Points Detection

The first step is the detection of the important main points of the fingerprints cores and delta points detection. These points are called reference points or global features data of the fingerprint images. The orientation field is used in 8x8 block-wise to estimate reference points in robustness [8, 9].

Let image I with size $w_0 \times h_0$, then size $(\Theta) = w \times h$. To find the orientation of the point (i, j) is denote as $\Theta(i, j) (1 \leq i \leq h, 1 \leq j \leq w)$. To find the heuristic direction, EDF use the following equation.

$$\mathrm{EDF}(i, j) = \left(2\Theta(i, j) - \frac{\pi}{2}\right) \bmod 2\pi \qquad (1)$$

Be the x, y as the image coordinate system, and denote $P_0 = (x_0, y_0)$ as the start point and to find the direction of that point use

$$\alpha_0 = EDF(y_0, x_0) \quad (2)$$

To walk to the next point $P_1 = (x_1, y_1)$, continue with

$$(x_1, y_1) = \begin{cases} (x_0, y_0 - 1) & \text{if}(\frac{\pi}{4} \le \alpha_0 < \frac{3\pi}{4}) \\ (x_0 - 1, y_0) & \text{if}(\frac{3\pi}{4} \le \alpha_0 < \frac{5\pi}{4}) \\ (x_0, y_0 + 1) & \text{if}(\frac{5\pi}{4} \le \alpha_0 < \frac{7\pi}{4}) \\ (x_0 + 1, y_0) & \text{otherwise} \end{cases} \quad (3)$$

Then continue to the end road point Pk and the center point of the road Pc can be calculated by

$$x_c = \frac{1}{k - i_0 + 1} \sum_{j=i_0}^{k} x_j,$$

$$y_c = \frac{1}{k - i_0 + 1} \sum_{j=i_0}^{k} y_j \quad (4)$$

The resulted detected point of the fingerprint images for both contact-based and contactless are shown in figure 1.

(a) (b)

Figure 1. Reference points of (a) Contact-based fingerprint and (b) contactless fingerprint

After getting the reference points, the images are cropped to normalize depend on these identified points and the main part of resulted images are shown in Figure 2.

(a) (b)

Figure 2. Extracted image from the reference point (a) Contact-based fingerprint and (b) contactless fingerprint

3.2. Minutiae Extraction

Since minutiae information is highly significant, most popular, and reliable features for AFRS, and the method is adapted from [10]. Firstly, before the minutiae extraction algorithm, MEA is applied, Gabor Filter is used to enhancing the image quality as in [11]. After getting the binarized image, the morphological thinning operation is performed to get the ridge structures as 1-pixel thickness, known as the skeleton, to improve minutiae detection. The resulted thinned image has pixel, p and it is analyzed to find the location of the minutiae. This is done with an 8-neighborhood (3x3 window with center p), it circularly traverses with counter-clockwise to produce the crossing number. Then the minutiae point can be found with the following equation.

$$cn(p) = \frac{1}{2} \sum_{i=1,\ldots 8} |val(p_{(i \bmod 8)}) - val(p_{i-1})| \quad (5)$$

where $val \in \{0,1\}$ is the intensity value of the binary image pixel.

But there may be a lot of minutiae and need to be clean the false minute that can degrade the performance and reduce the complexity and cause misclassification. Therefore, cleaning for noise minutiae points is performed and finally the termination and bifurcation points are obtained and the sample images for both contactless and contact-based of the fingers are shown in Figure 3.

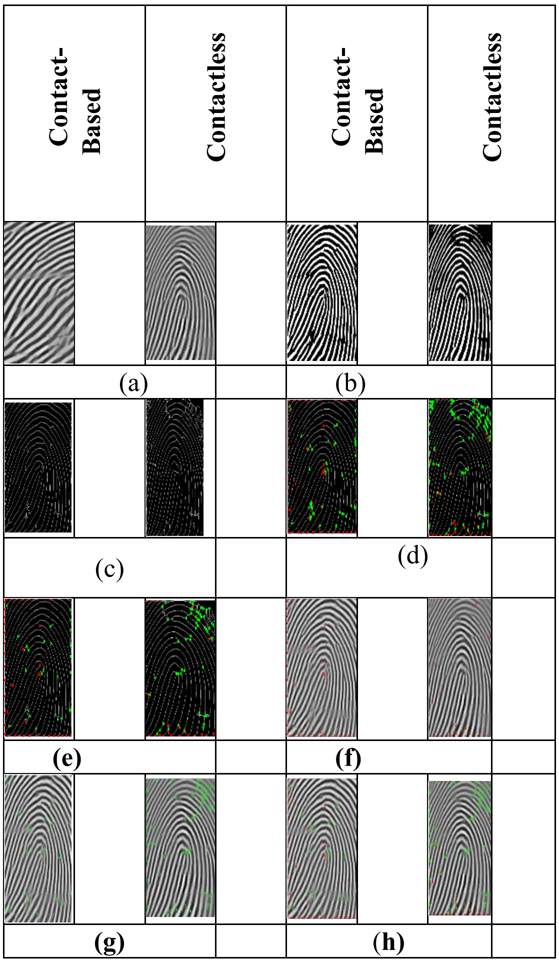

Figure 3. Sample images of the person 1 finger for Minutiae Extraction (a) Enhance (b) Binary (c) Thinn (d) Find Minutiae (e) Clean Minutiae (f) Termination (g) Bifurcation (h) Termination and Bifurcation

3.3. Feature Extraction

After getting the clean minutiae values, the features can be extracted. Although the values form the extracted minutiae are much less than the image pixel values, there may be problems of complexity in terms of both accuracy and time taken for very large datasets. The minutiae output for the first image of the person 336 is the 138x6 dimensional arrays and for six image samples, there may be (138x6x6) for that person. Therefore, the best features are needed to be extracted. Moreover, the extracted features should be suitable not only for the images from the same sensor but also for those fingerprints from the different sensors to get the sensor interoperability system. Therefore, only the information that can present the fingers is extracted from the image instead of using all the minutiae information. The information includes the total number of termination points, ridges, bifurcation point, loop, core, and delta point. The total number of 10 features is collected from the corresponding minutiae to reduce the dimension of the instances in order to improve the performance. Therefore, for each person, there may be (6x10) dimensions and can be calculated how much reduced the complexity and maybe a beneficial mechanism for each large datasets of biometrics.

3.4. Classification

Classification for minutiae features is done using the state-of-the-art machine learning classifier, Random Forest decision trees [12] instead of pattern vision classification. Therefore, the processing time can be reduced other normal pattern matching algorithm and a more suitable mechanism for the large volume of image processing databases in immediate response.

4. Experimental Evolution

4.1. Dataset Description

The database used in this experiment is “PolyU Contactless to Contact-Based Fingerprint Database” from the Hong Kong Polytechnic University [2]. These images are obtained with the low-cost camera and intend to be published available for standard performance comparison in fingerprinting. There are total numbers 2976 of 2D contactless and 2976 of corresponding contact-based images of the fingerprint taken from 336 volunteer people. The six numbers of fingerprints were collected from each person. To find the effectiveness of the proposed system, the database with 1800 2D contactless fingerprints and corresponding contact-based fingerprints from different 300 clients are prepared.

These datasets are prepared as others to compare the results of other previous researches.

4.2. Result Evaluation

The database used in the paper is originally permitted for university used only and publicly available in 2017 and most of the previous papers are evaluated using all the datasets. This experiment is the comparison for the proposed system and the previous result work for the PolyU dataset. The datasets are used the same as the previous works and the results are shown in Table 2. The experiments are carried out a contact-based system for the normal sensor, and cross-matching performance for different sensors to get the sensor interoperability ability. Therefore, the contact-based fingerprint images are trained, and the contactless images are tested against those contact-based sensor images.

As can be seen from Table 2, even the results for the contact-based achieve performance higher than the others, the cross-matching for contactless to contact-based can’t be compared with the work of RTPS+DCM minutiae & ridges in [2].

Table 2. Performance comparison for the previous system and proposed system

Works	Technology used	Accuracy (%)	
		Contact-based	Cross matching
Paper [13], 2007	NIST	76.44	16.61
Paper [14], 2003	thin-plate spline model	86.50	44.22
Paper [15], 2010	Minutia Cylinder-Code (MCC)	78.02	19.50
Paper [2], 2018	TPS+DCM	92.11	-
	RTPS+DCM	94.11	-
	TPS+DCM with minutiae	-	54.55
	TPS+DCM minutiae & ridge	-	61. 17
	RTPS+DCM minutiae	-	60.39
	RTPS+DCM minutiae & ridges	-	66.67
Paper [6], 2019	CNN with minutiae & ridge	-	64.59
Proposed System	Feature Selection +RF	100	65.98

5. Conclusion

This paper proposed the contactless fingerprint recognition framework that is essentially the requirement for today's technology application world, big data platform. The mechanism is intended to reduce the complexity of both pieces of training and testing process, in addition, to improve the performance in terms of accuracy and storage spaces, as there is no need to store the contactless fingers that take the high volume of storage places. However, the cross-matching accuracy can't be deployed for the real-world application and need to improve the acceptable performance and this may be the future work by using the other pattern matching theories for the small main extracted parts.

Acknowledgment

Authors want to acknowledge to the Hong Kong Polytechnic University for developing and sharing of contactless 2D Fingerprint Images Database in the public domain to further advance research in the fingerprint area.

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