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A Survey on 2D and 3D Contactless Fingerprint Biometrics: A Taxonomy, Review, and Future Directions

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ABSTRACT Contactless fingerprint biometrics has achieved rapid development in the past decades thanks to its inherent advantages, such as no physical contact between a finger and a sensor, no contamination by latent fingerprints, and more hygienic. These advantages have paved the way for new 2D or 3D contactless fingerprint-based applications and have promoted a larger number of academic publications in recent years. Therefore, it is necessary and important to conduct a comprehensive survey on contactless fingerprint biometric technology, review the latest research findings on 2D and 3D contactless fingerprint recognition systems, and point out the future development direction of contactless fingerprint biometrics. In this work, a comprehensive survey is presented to review the 2D and 3D contactless fingerprint biometrics from four essential aspects: contactless fingerprint capture, fingerprint preprocessing, feature extraction, and template comparison. To serve as a good reference, we provide a well-structured taxonomy about contactless fingerprint biometrics. We also identify related research problems and future research directions.

INDEX TERMS Biometrics, contactless fingerprint, 2D contactless fingerprint, 3D contactless fingerprint, 3D fingerprint reconstruction.

I. INTRODUCTION

A. BACKGROUND

A fingerprint is one of the most popular and reliable biometric traits and has been successfully equipped into various applications for identity verification (one-to-one comparison) or identification (one-to-many comparison), such as building access control, mobile products, and contactless payment cards [1], [2]. As an attractive alternative to conventional password-based verification, using fingerprints in these applications for identity verification is convenient because fingerprints cannot be forgotten. In forensics and law enforcement, a fingerprint is also one of the important biometric traits for identification as a fingerprint is considered to be unique and consistent throughout a person's life.

Currently, most of these applications are based on contact fingerprints (such as live-scan and wet-inked fingerprints), where the fingerprint capture process typically requires physical contact between a finger and the surface of a sensor. Although contact fingerprint images are likely to possess relatively high-contrast ridges and valleys, the physical contact during the fingerprint acquisition simultaneously incurs some issues [2], [3]. Firstly, the captured fingerprints are likely to be contaminated by the latent fingerprints left by previous users on the sensor surface [4]. Either this will result in bad-quality fingerprint images, or it will waste time cleaning the sensor surface. Secondly, because the pressure applied on the surface of the sensor is different during the capture process, fingerprints with different degrees of nonlinear distortion will be produced. This will degrade the comparison accuracy. More importantly, pathogens such as coronaviruses may spread through the sensor surface, which poses hygienic and even pandemic risks such as COVID-19.

To address these issues raised in the contact fingerprint recognition systems, contactless ones have been proposed in recent years [5]–[15]. The contactless fingerprint recognition systems are also an important component of *Next-Generation*

Fingerprint Technologies proposed by the National Institute of Standards and Technology (NIST).[1] Because there is no any physical contact between a sensor and a finger during the acquisition of contactless fingerprints, contactless fingerprint recognition systems can effectively address the aforementioned issues. In addition, contactless fingerprint recognition systems have more potential advantages. For example, contactless fingerprints captured by high-resolution cameras can provide more details besides the ridges and valleys. These major advantages pave the way for new contactless fingerprint-based applications and have inspired a large number of publications in recent years. Therefore, it is necessary and significant to investigate the contactless fingerprint biometrics to review the latest research results and point out the future development direction of the contactless fingerprint biometrics.

B. MOTIVATION

To illustrate our motivation and differentiate our survey from other surveys, we provide a summary of the related surveys. In 2009, Parziale *et al.* [16] investigated the challenges of contactless fingerprint recognition systems in terms of fingerprint capture, data format compatibility and the design of contactless fingerprint systems. However, this work mainly focuses on the capture of 2D and 3D contactless fingerprints. Besides, for 3D fingerprints, it mainly introduced stereo-vision-based methods. In 2012, Khalil *et al.* [17] reviewed contactless fingerprint preprocessing techniques for fingerprints captured by a mobile phone. This work covers some issues related to 2D contactless fingerprint preprocessing, but it lacks the introduction to the essential technologies of 3D contactless fingerprint. In 2014, Labati *et al.* [18] provided a brief introduction about 2D and 3D contactless fingerprint recognition technologies. This work mainly focuses on the introduction of unwrapping algorithms that transform the contactless fingerprint images to contact-equivalent fingerprint images. It fails to provide a comprehensive survey on 3D contactless fingerprints in terms of 3D acquisition methods, 3D features, and 3D template comparison. In 2019, Labati *et al.* [19] reviewed the methodologies of fingerprint biometrics targeted smartphones. It mainly focuses on the 2D contactless fingerprint recognition systems in terms of image acquisition, preprocessing, and template extraction and comparison. Similar to the work in [18], there lacks a comprehensive introduction and discussion about 3D fingerprints. In 2021, Priesnitz *et al.* [20] provided an overview of contactless fingerprint recognition. But this work only focuses on 2D contactless fingerprint biometrics, and does not cover 3D contactless fingerprint biometrics. In summary, the related surveys did not provide a comprehensive review on contactless fingerprint biometrics covering the latest 2D and 3D fingerprint technologies.

Therefore, it is necessary and significant to conduct a comprehensive survey on the contactless fingerprint biometrics to review the latest research findings on 2D and 3D contactless fingerprint recognition systems, and point out the future development direction of the contactless fingerprint biometrics. In this work, a comprehensive survey is presented to review the 2D and 3D contactless fingerprint biometrics covering fingerprint capture, fingerprint preprocessing, feature extraction, template comparison, and open research directions. To serve as a good reference, we provide a well-structured taxonomy about contactless fingerprint biometrics.

C. MAIN CONTRIBUTION

This work is to provide a comprehensive survey on contactless fingerprint recognition systems, including 2D contactless fingerprint recognition systems and 3D contactless fingerprint recognition systems. The main contributions of this study are as follows:

- We summarize the state-of-the-art 2D contactless fingerprint recognition systems, covering each stage from the image acquisition to template comparison and anti-spoof.
- We provide a comprehensive overview on 3D fingerprint recognition systems, especially the 3D fingerprint reconstruction technologies, including stereo vision based methods, structured light scanning based methods, and photometric stereo based methods.
- We propose a taxonomy to systematically present the 2D and 3D contactless fingerprint recognition systems.
- We identify open research problems existing in the current contactless fingerprint recognition system and discuss future research directions for these open problems.

The rest of this paper is organized as follows. Section II presents the proposed taxonomy to contactless fingerprint biometrics. In Section III, we introduce the acquisition of contactless fingerprints, including 2D and 3D fingerprints. Section IV discusses the preprocessing of 2D and 3D contactless fingerprints. In Section V, we mainly focus on the review of feature extraction in 2D and 3D fingerprints. Template comparison of 2D and 3D fingerprints is presented in Section VI. Finally, we provide the open research problems for future research and summarize the survey in Section VII.

II. TAXONOMY OF CONTACTLESS FINGERPRINT BIOMETRICS

Based on the characteristics of contactless fingerprint biometrics, we propose a taxonomy emphasizing 2D and 3D contactless fingerprint biometrics, as shown in Fig. 1. In this taxonomy, we focus contactless fingerprint biometrics on four aspects: 1) contactless fingerprint acquisition, 2) contactless fingerprint preprocessing, 3) 2D and 3D feature extraction, and 4) contactless fingerprint comparison. Contactless fingerprint acquisition reviews the acquisition of 2D and 3D contactless fingerprints, which provides a comprehensive comparison of state-of-the-art 3D contactless reconstruction methods. In contactless fingerprint preprocessing, we summarize four key stages, including fingertip extraction, ridge orientation estimation, ridge frequency estimation, and

[1] https://www.nist.gov/programs-projects/next-generation-fingerprint-technologies

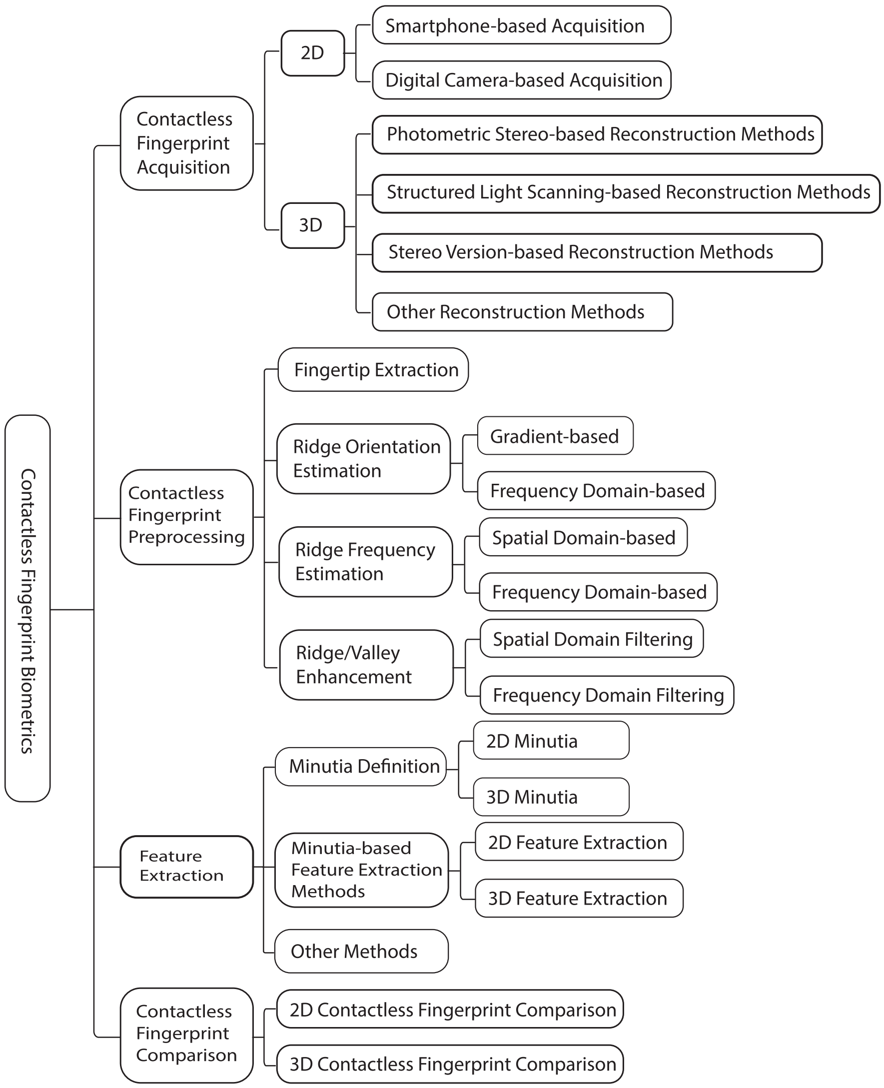


FIGURE 1. Proposed taxonomy to contactless fingerprint biometrics.

ridge/valley enhancement. Feature definition and extraction are then reviewed for 2D and 3D contactless fingerprints. Finally, we review 2D and 3D contactless fingerprint recognition.

III. CONTACTLESS FINGERPRINT CAPTURING TECHNIQUES

A. 2D CONTACTLESS FINGERPRINT CAPTURING TECHNIQUES

2D contactless fingerprint acquisition is mainly based on optical devices, such as a camera or a lens. The acquisition can be divided into two categories: 1) smartphone-based acquisition and 2) digital camera-based acquisition.

1) SMARTPHONE-BASED ACQUISITION

As smartphones or mobile phones are usually equipped with high-quality cameras and are widely available, they are utilized to capture 2D contactless fingerprints in the literature [21]–[28]. Derawi *et al.* [21] evaluated the performance of a contactless fingerprint recognition system based on 1,320 fingerprint images captured by a Nokia N95 and a HTC Desire under normal lighting conditions. This work pointed out that the image quality is likely to be affected by the embedded flash. Differently, Stein *et al.* [22] captured 2D fingerprint images with embedded flash in a dark environment. The experiment showed that using the flash spotlight in dark environments can significantly reduce camera noise, thereby improving the image quality. Sankaran *et al.* [26] investigated the influence of environmental illumination and background on contactless fingerprint images captured by a smartphone. The experiment showed that not only illumination but also backgrounds play a strong influence on the image quality. To capture a high-quality fingerprint image, video-based contactless fingerprint recognition systems were developed in the literature [23], [24]. In these systems, a high-quality fingerprint

TABLE 1. Comparison of 3D Fingerprint Reconstruction of the State-of-The-Art Methods

Categories	Senor Types & Ref.	Reconstruction Time	Development Platform	Indirect Accuracy*		Relative Cost	Relative System Size
				EER** (%)	Ridge/Valley Recovery		
Photometric Stereo	a camera [43]	~ 180s for 60K points	Matlab, CPU@2.7 GHz	nul	yes	low	small
	a camera [11]	~ 7.5s for 2.8M points	i5-7200 CPU@2.50 GHz	1.02			
	a camera [37]	~ 3s for 1.2M points	i7-4770 CPU@3.40 GHz	protocol A: 1.41 protocol B: 1.25			
Structured Light Scanning	a DLP projector & a camera [7]	~ 1s for 5M points	no details	nul	yes	high	bulky
	a DLP projector & a camera [38]	~ 0.5s for 450K points	C++ and no more details	nul			
Stereo Vision	five cameras [41]	computationally expensive	no details	nul	no	medium	medium
	three cameras [10]	~ 90s for 45K points	Matlab, T9600 CPU@2.80 GHz	nul			
	two cameras [42]	~ 24s for 1.2M points	Matlab, Xeon CPU@3.60 GHz	dataset A: 0.06 dataset B: 1.2			
	two cameras [15]	~ 0.1s for 1.2M points	Matlab, i7-5500U CPU@2.4 GHz	0.66	yes		

* Note: As there is no consistent quantification of 3D fingerprint reconstruction accuracy, we compare the accuracy in an indirect way in terms of EER and ridge/valley recovery.** Note: the values of EER come from the corresponding original papers and are calculated according to different datasets and protocols.

image is selected from frames of a short video. Alkhathami *et al.* [25] proposed generating roll-equivalent fingerprint images by mosaicking three images captured sequentially with a smartphone. Carney *et al.* [27] proposed a multi-finger contactless fingerprint capture system based on smartphones. As an advantage, up to five fingerprints can be extracted from a multi-finger image.

2) DIGITAL CAMERA-BASED ACQUISITION

Compared with smartphone based acquisitions, digital camera based acquisitions are more flexible in system design [29]–[35]. In digital camera-based systems, white or color LEDs are usually utilized to provide predicable lighting. Wang *et al.* [29] designed an optical, contactless, compact fingerprint capture system which is mainly composed of three cameras and some color LEDs. As three cameras were used in this system to capture different views of a finger, the placement of a finger during the capture process is more user-friendly. Similarly, Khodadoust *et al.* [35] also developed a three-camera (PULNIX TM-7EX) device with blue light-emitting diodes to capture multiple views of a finger. Compared with the system in [29], this system can capture finger-vein and finger-knuckle images. Noh *et al.* [30] developed a contactless capture system equipped with a charge-coupled device (CCD) camera, a stepping motor, a mirror, and green LEDs. As an advantage, this system can capture five fingerprint images once time. But the capture time is up to 2.5 seconds. The experiments showed that this system can capture high-quality and high-contrast fingerprint image. Tsai *et al.* [31] built a contactless fingerprint reader based on a digital variable-focus liquid lens for fast focus plane scanning. The capture of the multiple focal planes is approximately 0.2 s. Then a high-quality image with proper focus is selected to extract a fingerprint. Raghavendra *et al.* [32] developed a capture system consisting of a CMOS camera, 40 near infrared LEDs, and visible light LEDs. As an advantage, finger vein can be captured simultaneously. Different from the aforementioned systems, Weissenfeld *et al.* [33] designed a mobile system equipped with a camera, a quad-core CPU and an accelerator FPGA. This system is also designed to capture four fingerprints once time. Genovese *et al.* [34] proposed a capture system equipped with a high-resolution camera and LEDs. Compared with other capture systems, this system can capture and extract sweat pores in a fingertip.

B. 3D CONTACTLESS FINGERPRINT CAPTURING TECHNIQUES

3D fingerprint reconstruction is an essential component of 3D fingerprint recognition systems. In recent years, several methods have been proposed to construct 3D fingerprints, which can be classified into three categories according to their imaging techniques: 1) photometric stereo [11], [36], [37]; 2) structured light scanning [7], [38]–[40]; and 3) stereo vision [10], [15], [41], [42]. Table 1 gives a brief review of the state-of-the-art 3D fingerprint reconstruction methods.

1) PHOTOMETRIC STEREO BASED 3D FINGERPRINT RECONSTRUCTION

Photometric stereo-based methods need to capture multiple 2D fingerprint images under different illuminations by using a fixed high-speed camera. The principle of photometric stereo is that 3D surface reflectance can be calculated by its orientation with respect to the observer and the light source [44]. Many photometric stereo-based methods were proposed to reconstruct 3D fingerprint information by calculating the surface normal [11], [36], [37], [43]. The hardware system of these methods is usually composed of a high-speed camera and several LEDs. The advantage is that these systems are generally low-cost and possesses a compact size. However, these methods are likely to be time-consuming due to the extensive computation of surface normal for each pixel. For example, the method in [43] showed that about 180 seconds are needed for reconstructing a 3D fingerprint with the resolution of 300 × 200. Moreover, these methods require large random-access memory to store the pre-calibrated data [11], [37].

2) STRUCTURED LIGHT SCANNING BASED 3D FINGERPRINT RECONSTRUCTION

The system of capturing 3D fingerprint based on structured light scanning is usually comprised of several high-speed cameras and a DLP projector. During the capture process, multiple 2D fingerprint images are captured under pattern illuminations. Its principle is triangulation, where 3D depth information is calculated according to the point correspondences between images. In methods [7], [40] and [38], the correspondence between observed points and projected pattern points is pre-encoded precisely, thus 3D fingerprints are reconstructed by measuring the deformation of the projected patterns. The advantage is that they can recover ridge-valley details and achieve relatively accurate 3D depth information. However, the hardware system of these methods is expensive and bulky due to the special projector and high-speed cameras.

3) STEREO VERSION BASED 3D FINGERPRINT RECONSTRUCTION

stereo vision-based 3D fingerprint systems are usually comprised of two or multiple cameras. During the capture process, 2D fingerprint images are captured from different views. The 3D fingerprints are reconstructed by calculating 3D depth information between corresponding points according to the triangulation principle. The advantage is that the systems are simple, low-cost and relatively compact. However, current methods are usually time-consuming because of the extensive computation of the correspondences between pixel points. To speed up the calculation, Liu *et al.* [10] proposed to establish the correspondence based on minutiae and SIFT points [45] to model the 3D fingerprint surface. Labati *et al.* [42] proposed a 3D fingerprint reconstruction system with only two views and used a correlation-based algorithm to establish the correspondence. However, these methods take 1.5 minutes to construct one 3D fingerprint. Besides, these methods fail to recover ridge-valley details since the correspondence establishment is based on blocks rather than pixels. Compared with the stereo vision-based methods, Yin *et al.* [15] proposed a ridge-valley-guided method, which can achieve the details of ridges and valleys with a low cost of reconstruction time.

4) OTHER RECONSTRUCTION METHODS

In addition to the aforementioned methods, other methods based on optical coherence tomography (OCT) and ultrasonic imaging (UI) have been proposed for 3D fingerprint reconstruction [46]–[50]. The OCT-based methods in [46], [47] calculate 3D fingerprint information based on interferometry principle [51]. As an advantage, these methods are accurate and have potential capability against spoofing attacks [52]. However, the cost of this type of systems is particularly high, at least $7000 according to the report in [53]. The UI-based methods [48]–[50] calculate 3D fingerprint information by measuring acoustic time-of-flight. The capture systems in these methods are at low cost, but the capture process is usually time-consuming, taking about 5 seconds to produce a 3D fingerprint with the resolution of 1000 dpi [50]. Besides, the UI-based methods are not completely contactless because they require pressing fingers against a plate during the acquisition process. In addition, Galbally *et al.* [54] proposed a 3D fingerprint capture system based on laser sensing. As an advantage, this system can directly capture the 3D fingerprint models as point-clouds.

C. SUMMARY

In this section, we reviewed the acquisition methods of 2D and 3D contactless fingerprints. In the design of 2D acquisition systems, smartphone-based systems are more portable and convenient. Compared with smartphone-based acquisition, digital camera-based system are more flexible in the system design. In the design of 3D acquisition system, structured light scanning can produce reconstructed results with ridges and valleys. But the cost of this type of systems is likely relative high due to the projector and high-speed camera. The photometric stereo and stereo vision tend to be time-consuming.

IV. PREPROCESSING OF CONTACTLESS FINGERPRINT

The preprocessing of contactless fingerprints aims to improve the contrast between ridges and valleys to facilitate the subsequent feature extraction. Compared with contact fingerprint images such as rolled fingerprints in which the ridges are usually in black and the valleys are usually in white, contactless fingerprint images are of relatively low-contrast between ridges and valleys, as shown in Fig. 2. The preprocessing of contactless fingerprints contains four main components: 1) extraction of a fingertip, 2) estimation of ridge orientation, 3) estimation of ridge frequency, and 4) enhancement of ridges and valleys

A. EXTRACTION OF FINGERTIP

The region of interest (ROI) of a fingerprint image is the fingertip area covering ridge-valley pattern or feature points such as minutiae which can be used to effectively compare two fingerprints. Most methods extract the ROI based on the skin color [23], [25], [26], [56]. Ravi *et al.* [56] utilized a threshold approach based on the skin color to extract the ROI from the background. This method is very simple, but this extraction method suffers from the image background. Stein *et al.* [23] used a fixed threshold to extract the RIO on the red-channel of a fingerprint image. To improve this approach, Alkhathami *et al.* [25] and Sankaran *et al.* [26] adopted

(a) Contact fingerprint 1_1 from FVC2002-DB1-A [55]

(b) Contactless fingerprint 1_1_1_0 from dataset [9]

FIGURE 2. Comparison of a contact fingerprint and a contactless fingerprint: (a) a contact fingerprint image with image ID 1_2 from FVC2002-DB1-A [55]; (b) a contactless fingerprint image with image ID 1_1_1_0 from a benchmark dataset [9].

adaptive threshold approaches to segment the ROI from the background. Differently, Noh *et al.* [30] proposed using local image contrast and ridge frequency to extract the ROI. The final ROI was obtained by combining the extracted regions by these two approaches. Compared with simple threshold approaches, Wasnik *et al.* [24] proposed an approach based on histogram equalization and K-means clustering to segment the ROI and the background. To effectively extract the ROI, Yin *et al.* [2] proposed a simple but effective method based on a convolutional neural network by learning the patterns of fingertip areas and knuckle areas.

B. ESTIMATION OF RIDGE ORIENTATION

The ridge orientation is an essential characteristic of fingerprints, which indicates the ridge flows. The methods can be typically divided into two categories: 1) gradient-based methods and 2) frequency domain-based methods.

1) GRADIENT-BASED METHODS

Gradient-based methods are widely used to estimate ridge orientation in the area of contactless fingerprints [2], [13], [25], [56], [57]. The gradient in a local region represents the ratio of intensity change and is perpendicular to the ridge flow. In 1987, Kass *et al.* [58] proposed a robust method for local gradient estimation. Liu *et al.* [57] used a gradient-based method to estimate local orientation for contactless fingerprints. Yin *et al.* [2] developed an orientation estimation method based on guided-image filtering and gradient estimation. There are two main advantage to gradient-based methods: 1) the local orientation estimation is computation-efficient and 2) it is robust to image noise in local regions.

2) FREQUENCY DOMAIN-BASED METHODS

Kamei *et al.* [59] proposed a method based on 16 directional filters in the frequency domain. The optimal local orientation is determined by the orientation of the filter with the highest response in the local region. Smoothing local orientation make it robust to image noise. Chikkerur *et al.* [60] proposed an orientation estimation method based on Short Time Fourier Transform (STFT) analysis. Local orientation of each small block is first calculated by the STFT analysis. Then, the orientation map is calculated by sliding window. The advantage is that this method is robust to image noise. Wang *et al.* [61] proposed a fingerprint orientation model based on 2D Fourier expansions (FOMFE). As an advantage, the FOMFE can reliably describe the overall ridge topology and is robust to image noise. Larkin [62] introduced an orientation estimation method based on two energy operators. The advantage is that this method provides uniform and scale-invariant orientation estimation.

C. ESTIMATION OF RIDGE FREQUENCY

The local ridge frequency is another essential characteristic of fingerprints, which indicates the number of ridges per unit length orthogonal to the local ridge orientation. The methods can be typically divided into two categories: 1) spatial domain-based methods and 2) frequency domain-based methods.

1) SPATIAL DOMAIN-BASED METHODS

Hong *et al.* [63] proposed calculating local ridge frequency by measuring the average number of pixels between two consecutive peaks in a local window orthogonal to the local ridge orientation. This method is simple, but in noisy contactless fingerprint images, it is difficult to reliably measure the average number of pixels between two consecutive peaks. To address this problem, Yang *et al.* [64] proposed using a fitting approach based on x-signature. Compared with Hong *et al.* [63], the fitting method is to calculate the first and second order derivatives. The advantage is this method is more reliable and is robust to image noise. Yin *et al.* [12], [13] modified this approach to estimate the local ridge frequency for contactless fingerprint images. However, these methods are likely to suffer from non-well sinusoidal-shaped surfaces.

2) FREQUENCY DOMAIN-BASED METHODS

Jiang [65] proposed a method for estimating the local ridge frequency by using higher order spectra. In this method, the signal of ridge frequency is effectively improved by using the second and third harmonic. The advantage is that this method is robust to image noise and provides a reliable estimation for bad quality fingerprint images. Kovács-Vajna *et al.* [66] proposed an approach by searching the maxima in the Fourier power spectrum of a local block. Chikkerur *et al.* [60] presented a method based on Short Time Fourier Transform to estimate the local ridge frequency. The advantage of these methods is that frequency estimation in frequency domain is robust to noise and is usually time-saving.

D. ENHANCEMENT OF RIDGES AND VALLEYS

The enhancement of ridges and valleys aims to improve the contrast between ridges and valleys and generate a gray or binary image. According to the filtering domain, the enhancement methods can be divided into two categories: 1) spatial domain filtering and 2) frequency domain filtering.

1) SPATIAL DOMAIN FILTERING

O'Gorman *et al.* [67], [68] firstly proposed using bell-shaped filters to improve the contrast between ridges and valleys of fingerprint images. These filters are defined by the ridge orientation and frequency, and 16 filters with different orientations are pre-built. To reduce computational complexity, the ridge frequency is set to a constant value. However, it simultaneously results in imprecise filtering result in the regions with different local ridge frequencies. Hong *et al.* [63] developed a similar enhancement approach based on Gabor filters. Compared with the filters in Ref. [67], [68], the filters in this method are dynamically determined by the local ridge orientation and frequency. The advantage is that the filter can fit the local pattern well, so as to obtain a more accurate filtering result than [67], [68]. However, adaptively calculating local ridge frequency is time-consuming. In addition, the filtering result tends to be poor in some regions where the local ridge pattern is not similar to a sinusoidal pattern. To address this problem, Greenberg *et al.* [69] proposed reducing the value of the standard deviations of Gaussian envelope along the x-axes. To improve the enhancement in regions that is not similar to a sinusoidal pattern, Yang *et al.* [64] proposed another Gabor filter-based method. In this method, different values are assigned to the positive and negative ridge frequencies, respectively. Hence, this method can achieve good results in regions with different positive and negative ridge frequencies. However, this method does not perform well in local regions with non-wave-shaped pattern, as it is usually difficult to estimate the local ridge orientation and frequency in those regions.

Compared with the squared Gabor filters used in [63], [64], [67], Zhu *et al.* [70] presented a circular Gabor filter-based method. In this method, a circular mask is used for each local region to eliminate the blocky effect caused by a square mask. However, due to the average of frequency, filtering results in some regions are likely to blur.

To address the distortion in contactless fingerprint images, Zhang *et al.* [10] proposed a Gabor filter-based method. In this method, the nearest neighbor approach is introduced to smooth the local orientations in particular regions, and a quadratic function and a quadratic curve are utilized to estimate the local ridge frequency. However, the estimation of the local ridge orientation and frequency suffers from image noise. Besides, it is difficult to balance the filtering performance between denoising and accuracy. Liu *et al.* [57] developed another Gabor filter-based method for contactless fingerprint enhancement. Their experiments showed that this method achieves good enhancement results. However, this method is time-consuming, taking about 10 seconds for enhancing one image.

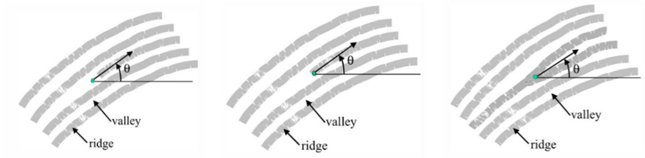
2) FREQUENCY DOMAIN FILTERING

Besides the aforementioned methods based on spatial domain filtering, frequency domain filtering is also widely utilized for fingerprint enhancement. Sherlock *et al.* [71] introduced Fast Fourier Transform into fingerprint image enhancement. In this method, the Fourier transform result of a fingerprint image is first processed by n pre-defined global Fourier filters with variant ridge orientations. Then, the enhancement result is finally determined by the result of the filter whose orientation is closest to the local ridge orientation. As an advantage, it is faster than those methods based on spatial domain filtering. However, the constant ridge frequency used in these global Fourier filters tends to result in poor filtering in regions with significantly different local ridge frequencies.

Watson *et al.* [72] proposed an enhancement method in the Fourier domain, where the local ridge frequency and the local ridge orientation are no need to compute explicitly. In this method, a fingerprint image is first divided into a series of overlapped blocks. For each block, a fast Fourier filter is utilized to calculate its 2D discrete Fourier transform. Then, the new transform is obtained by multiplying the power spectrum and the 2D discrete Fourier transform. The enhancement image is finally generated by calculating the real part of the inverse transform. As an advantage, this method is simple. However, the block-based scheme used in this method tends to generate blocky effect in the enhanced image, and this method fails in noisy regions. To address this issue, Chikkerur *et al.* [60] developed an enhancement method based on short-time Fourier Transform, which divides a fingerprint image into different overlapping blocks and calculates fast Fourier analysis on each block. The enhancement result achieved by this method is similar to that in [63]. As an advantage, it takes less time than the method in [63], and simultaneously generates the local direction and frequency in the Fourier analysis process. However, this method is likely to fail in the regions near singularity points. Jirachaweng *et al.* [73] proposed a similar method based on frequency domain filtering. The difference is that their block-wise filtering is processed in the discrete cosine transform domain instead of in the Fourier domain.

E. SUMMARY

In this section, we reviewed the contactless fingerprint preprocessing in four aspects: 1) fingertip extraction, 2) ridge orientation estimation, 3) ridge frequency estimation, and 4) ridge/valley enhancement. In the fingertip extraction, we analyzed and reviewed the color-based and pattern-learning-based methods. In the ridge orientation estimation, we reviewed the related methods from two categories: the gradient-based methods and the frequency domain-based methods. In the ridge frequency estimation, we reviewed the related methods from the spatial domain and frequency domain. In the ridge/valley enhancement, we reviewed and compared the related methods in spatial domain filtering and frequency domain filtering.



(a) Minutia of ridge ending (b) Minutia of ridge ending (c) Minutia of ridge bifurcation

FIGURE 3. **Minutia types defined in the standard IOS/IEC 19794-2:2011: (a)-(b) minutia of ridge ending, and (c) minutia of ridge bifurcation, where the dark curves are the ridges.**

V. FEATURE EXTRACTION

A. MINUTIA DEFINITION

1) 2D MINUTIAE

In the standard IOS/IEC 19794-2:2011 standard,[2] minutia feature points are defined into two types: ridge ending and ridge bifurcation. The ridge ending is referred to as a ridge skeleton endpoint or valley skeleton bifurcation, as shown in Fig. 3(a) and Fig. 3(b), respectively; the ridge bifurcation is referred to as a ridge skeleton bifurcation, as shown in Fig. 3(c). The origin of the coordinate system is placed in the upper left corner of a fingerprint image, with x-axis increasing rightward and y-axis increasing downward. A 2D minutia is typically defined by (x, y, θ, t), where x and y are the coordinates, $\theta \in [0, 2\pi]$ is the minutia direction, and t is the minutia type.

2) 3D MINUTIAE

A 3D minutia is a straightforward extension of a 2D minutia in 3D space. It is typically defined by $(x, y, z, \theta, \phi, t)$, where (x, y, z) are the coordinates in 3D space, θ and ϕ are the minutia's directions along the 3D ridge directions in 3D space, and t represents the minutia type [11], [15].

B. MINUTIA-BASED FEATURE EXTRACTION METHODS

1) 2D MINUTIA-BASED FEATURE EXTRACTION METHODS

For enhanced 2D contactless fingerprint images, feature extraction methods developed for contact fingerprints can be similarly applied to extract features [20]. According to the definition, the 2D minutia extraction can be roughly divided into two categories: thin-ridge-valley based extraction and pattern based extraction. In the thin-ridge-valley based extraction, ridges/valleys will be firstly binarized based on the enhanced contactless fingerprint images. Then, a thin ridge-valley map is obtained from the binary ridge-valley image by thinning the ridges and valleys. Finally, minutiae can be detected by counting the number of thin ridge pixels in the 8-neighborhood local window [74]. In the pattern based extraction, minutiae are extracted by comparing the ridge/valley pattern in a local window with the minutia definition. For example, in the method [75], ten ridge/valley patterns are defined to detect minutiae, including two ridge ending patterns and eight bifurcation patterns. As an advantage, the pattern based extraction does need thinning ridges/valleys. As a disadvantage, it is likely to generate fake minutiae. The pattern based MINDTCT algorithm [75] has been widely used to extract minutiae on enhanced contactless fingerprint images [12], [32], [76], [77]. Sisodia *et al.* [78] proposed a method based on thin ridges/valleys to detect minutiae. Tico *et al.* [79] proposed an orientation-based minutia descriptor which incorporates local information in a circular pattern around each minutia. Feng *et al.* [80] proposed a texture-based descriptor and a minutia-based descriptor. The texture-based descriptor is based on local ridge orientation and frequency information at sampling points around each minutia. The minutia-based descriptor is composed of a set of neighboring minutiae for each minutia. Cappelli *et al.* [81] proposed a minutia cylinder-code to represent each minutia. This code can effectively incorporate the local minutia distribution in terms of relative orientation and relative distance.

2) 3D MINUTIA-BASED FEATURE EXTRACTION METHODS

According to the definition of 3D minutiae, the detection of 3D minutiae can be established based on the 2D minutiae. Given a 2D minutia (x, y, θ, t), it needs to determine the values of z and ϕ for the corresponding 3D minutia. As z is the depth in 3D space, therefore it is easy to obtain the value of z according to the coordinates (x, y) of the 2D minutia. The value of ϕ can be determined by tracing the 3D fingerprint surface along the θ direction [11]. Lin *et al.* [37] proposed a Delaunay tetrahedron-based 3D minutia feature, which is defined as a convex polyhedron consisting of four triangular faces of 3D minutiae. As an advantage, this feature is time-saving when used in fingerprint alignment compared with the conventional 3D minutiae. However, its spatial topology is susceptible to spurious and missing 3D minutiae [82]. Liu *et al.* [83] proposed a 3D feature extraction approach based on the surface curvature of a 3D fingerprint, including the curve-skeleton and overall maximum curvatures. The curve-skeleton of a 3D fingerprint consists of representative vertical and horizontal lines. The overall maximum curvatures are modeled by a binary quadratic function. However, this representation achieved poor recognition accuracy [37], [83]. Yin *et al.* [15] proposed a novel 3D topology polymer (TTP) feature. As an advantage, the TTP features can encode the 3D topology of minutiae distribution by projecting the 3D minutiae onto multiple 2D planes. Ramya *et al.* [84] proposed using polynomial coefficients of a polynomial curve of a 3D fingerprint image as a template. The curve was calculated by the distance between minutiae and singular points.

C. OTHER FEATURE EXTRACTION METHODS

Hiew *et al.* [85] presented an approach based on block-wise Gabor-filter to build a feature descriptor by converting the magnitude into a scalar number. Then, the PCA was utilized to reduce the dimension of the descriptor. Wang *et al.* [86] proposed a feature representation approach based on local binary patterns and local gradient coding. Lin *et al.* [14] proposed

[2] https://www.iso.org/standard/50864.html

learning a representative feature based on a convolutional neural network. Sankaran *et al.* [26] presented a feature extraction approach based on networks to represent the local patterns. These networks consist of a set of wavelets which is stable to local affine transformation. As an advantage, the higher order network coefficients can offer translation and rotation invariant representation for contactless fingerprint images. Yin *et al.* [12] proposed using the ridge count between minutiae as a distortion-free feature representation. Wasnik *et al.* [24] proposed a feature extraction approach based on the eigenvalues of convolved images using multiscale second order Gaussian derivatives.

D. SUMMARY

In this section, we provided the definition of 2D minutia and 3D minutia and reviewed feature extraction methods. In the feature extraction, we emphasized the minutia-based feature extraction methods in 2D and 3D contactless fingerprints. Besides, other feature extraction methods which are not based on minutiae were also reviewed and discussed to provide a relatively comprehensive comparison.

VI. CONTACTLESS FINGERPRINT COMPARISON

A. 2D CONTACTLESS FINGERPRINT COMPARISON

Wang *et al.* [86] proposed a matching scheme for 2D contactless fingerprint based on histogram intersection, log-likelihood statistic, and Chi square statistic to match minutia descriptors. Labati *et al.* [87] presented an identification method based on a neural network classifier. The classifier was trained on a set of features, including minutiae, fingercodes [88], and HOG [89]. Scotti *et al.* [8] proposed a similar method based on a set of local features, including finger silhouette asymmetry and fingercodes [88]. Tiwari *et al.* [90] developed a method for mobile fingerprint images based on the scale-invariant robust feature [91]. Lee *et al.* [92] introduced a hardware-based contactless fingerprint recognition system in which multiple views of 2D fingerprint images are enhanced by an algorithm [63]. The contactless fingerprint recognition was established by compare multiple 2D contactless fingerprint using an algorithm [93]. Sano *et al.* [94] developed a contactless fingerprint recognition system by using a traditional greedy algorithm to obtain the minutiae correspondence. However, the recognition accuracy is not good.

Genetic algorithms (GAs) have been utilized to search the optimal geometrical transformation between two fingerprints [95], [96]. Yin *et al.* [12] propose a global similarity recognition method based on a GA to establish the minutiae correspondence. In this method, the contactless fingerprint comparison is formulated as a combinatorial optimization problem. The minutiae and the minutia-pairs relationship were used to represent the overall minutia topology.

B. 3D FINGERPRINT COMPARISON

Liu *et al.* [83] proposed a 3D fingerprint comparison approach based on the curve-skeleton and overall maximum curvatures of 3D fingerprints. Kumar *et al.* [11] proposed a comparison method based on aligning 3D minutiae in 3D space. A 3D minutia was presented by a 5-tuple composed of three coordinates and two ridge orientations in 3D space. This method is simple, but it is computationally expensive and time-consuming to align two sets of 3D minutiae during the fingerprint comparison. To reduce computational complexity, Lin *et al.* [37] proposed a matching algorithm based on 3D minutiae tetrahedron alignment. Yin *et al.* [15] proposed a 3D fingerprint comparison scheme using the LSA-R algorithm [81] based on the extraction of 3D topology polymer features. Zheng *et al.* [97] developed a contactless 3D fingerprint recognition method based on recovered surface normal and albedo information. However, this method is dependent on the 3D capture system as albedo information is used during the comparison.

C. SUMMARY

In this section, we mainly discussed and reviewed 2D contactless fingerprint matching and 3D contactless fingerprint matching. In the 2D contactless fingerprint matching, we mainly reviewed traditional transformation based matching methods, the neural network based methods, and GA based methods. In the 3D contactless fingerprint matching, we mainly reviewed and compared 3D minutia based matching and 3D representative feature based matching.

VII. SUMMARY AND OPEN RESEARCH DIRECTIONS

In this paper, we investigated the latest developments of the 2D and 3D contactless fingerprint biometrics and proposed a systematic taxonomy covering the primary components in contactless fingerprint biometrics. First, we provided a comprehensive overview on contactless fingerprint capture technologies, including 2D contactless fingerprint capture and 3D contactless fingerprint reconstruction. Especially for 3D contactless fingerprint reconstruction technologies, we thoroughly discussed three types of reconstruction methods, including photometric stereo, structured light scanning, and stereo vision, in terms of capture equipment, reconstruction time, and reconstruction results. Then, we presented an overview on the preprocessing of contactless fingerprint images, including extraction of fingertip, estimation of ridge orientation and frequency, and enhancement of ridges and valleys. Further, we discussed 2D and 3D feature extraction, including minutia-based methods and non-minutia-based methods. Finally, we provided an overview on 2D and 3D contactless fingerprint comparison.

Although the contactless fingerprint biometric technology has developed rapidly in recent years, there still exist some issues in terms of performance, security, and privacy in this research field. In the following discussion, we point out some open research questions and the corresponding potential directions.

- 2D contactless fingerprint acquisition. The existing technologies for 2D contactless fingerprint acquisition are mainly based on optical cameras (i.e., CCD and CMOS cameras). The fingerprint image is captured by the optical camera based on light reflection from the skin of the fingertip. The illumination hence plays an essential role in the capture process. The advantage is that it is simple and easy. As a disadvantage, the quality of 2D contactless fingerprint images suffers from the appropriate illumination. Therefore, it is necessary to develop an effective scheme to appropriately control the illumination. In addition, the distance between the sensor and the fingertip is also an important factor, which would result in the fingerprint image with quite different DPI. As 500 DPI is required in most recognition systems or software, such as NBIS[3] and Verifinger SDK,[4] an appropriate post-processing can be conducted to deal with this resolution issue.

- Hardware-oriented 2D contactless fingerprint acquisition. Because the contrast between ridges and valleys in contactless 2D contactless fingerprint images suffers from the existing optical camera-based acquisition, it would be very promising to develop hardware-oriented acquisition systems for high quality fingerprint image acquisition. Currently, in order to improve the contrast between ridges and valleys, software-oriented image processing technologies have been used to enhance 2D contactless fingerprint images. Two main problems raise in the software-oriented image processing. First, the enhancement of bad-quality images is limited. If the captured image is bad-quality (e.g., blurring), it is difficult to achieve a good one by using software-oriented image processing. Second, the software-oriented image processing for high-resolution fingerprint image is likely to be time-consuming. Therefore, it is promising to develop hardware-oriented capture systems which aim to directly obtain fingerprint images with high-contrast ridges and valleys.
- 3D fingerprint acquisition. Current 3D fingerprint acquisition systems are primarily based on optical cameras or DLP projectors. There are three main problems. There exist three key issues related to the state-of-the-art 3D fingerprint acquisition. Firstly, the size of capture systems tends to be bulky. For example, structured light scanning systems usually consist of at least a DLP projector and a camera. Second, the software-oriented 3D reconstruction is likely to be time-consuming because of the extensive computation of 3D cloud points. The photometric stereo based systems take more than 3 seconds [11], [37], [43]. The most important one is the reconstruction accuracy of 3D fingerprint reconstruction. Most existing methods still suffer from the bad-quality 2D images because they are primarily based on software-oriented reconstruction.
- Representation of 3D minutiae. Using 3D minutiae based alignment methods [11] for fingerprint recognition is likely to be computationally expensive. It is necessary to develop efficient and effective feature for 3D minutiae. Liu *et al.* [83] proposed one feature representation of 3D minutiae. However, this feature representation achieved poor performance. In recent years, deep neural networks have been proven to have a powerful ability to extract representative features. Therefore, it is an attractive solution to extract representative features for 3D fingerprints.

[3]https://www.nist.gov/services-resources/software/nist-biometric-image-software-nbis

[4]https://www.neurotechnology.com/verifinger.html

REFERENCES

[1] Q. N. Tran, B. P. Turnbull, and J. Hu, "Biometrics and privacy-preservation: How do they evolve?," *IEEE Open J. Comput. Soc.*, vol. 2, pp. 179–191, 2021, doi: 10.1109/OJCS.2021.3068385.

[2] X. F. Yin, Y. M. Zhu, and J. K. Hu, "Contactless fingerprint recognition based on global minutia topology and loose genetic algorithm," *IEEE Trans. Inf. Forensics Secur.*, vol. 15, pp. 28–41, 2020, doi: 10.1109/TIFS.2019.2918083.

[3] Y. Zhu, W. Zhou, X. Yin, and J. Hu, "3D Fingerprint," in *Encyclopedia of Cryptography, Security and Privacy*, S. Jajodia, P. Samarati, and M. Yung M., Eds. Berlin, Heidelberg: Springer, 2021, pp. 1–4, doi: https://doi.org/10.1007/978-3-642-27739-9_1513-1.

[4] Y. Zhu, X. Yin, X. Jia, and J. Hu, "Latent fingerprint segmentation based on convolutional neural networks," in *Proc. IEEE Workshop Inf. Forensics Secur.*, 2017, pp. 1–6.

[5] G. Parziale, *Touchless Fingerprinting Technology*. London, U.K.: Springer, 2008, pp. 25–48.

[6] H. Choi, K. Choi, and J. Kim, "Mosaicing touchless and mirror-reflected fingerprint images," *IEEE Trans. Inf. Forensics Secur.*, vol. 5, no. 1, pp. 52–61, Mar. 2010.

[7] Y. Wang, L. G. Hassebrook, and D. L. Lau, "Data acquisition and processing of 3-D fingerprints," *IEEE Trans. Inf. Forensics Secur.*, vol. 5, no. 4, pp. 750–760, Dec. 2010.

[8] R. D. Labati, A. Genovese, V. Piuri, and F. Scotti, "Contactless fingerprint recognition: A neural approach for perspective and rotation effects reduction," in *Proc. IEEE Symp. Comput. Intell. Biometrics Identity Manage.*, 2013, pp. 22–30.

[9] W. Zhou, J. Hu, I. Petersen, S. Wang, and M. Bennamoun, "A benchmark 3D fingerprint database," in *Proc. Int. Conf. Fuzzy Syst. Knowl. Discov.*, 2014, pp. 935–940.

[10] F. Liu and D. Zhang, "3D fingerprint reconstruction system using feature correspondences and prior estimated finger model," *Pattern Recognit.*, vol. 47, no. 1, pp. 178–193, 2014.

[11] A. Kumar and C. Kwong, "Towards contactless, low-cost and accurate 3D fingerprint identification," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 3, pp. 681–696, Mar. 2015.

[12] X. Yin, J. Hu, and J. Xu, "Contactless fingerprint enhancement via intrinsic image decomposition and guided image filtering," in *Proc. IEEE Conf. Ind. Electron. Appl.*, 2016, pp. 144–149.

[13] X. Yin, Y. Zhu, and J. Hu, "A robust contactless fingerprint enhancement algorithm," in *Proc. Mobile Netw. Manage.*, 2018, pp. 127–136.

[14] C. Lin and A. Kumar, "Contactless and partial 3D fingerprint recognition using multi-view deep representation," *Pattern Recognit.*, vol. 83, pp. 314–327, 2018.

[15] X. Yin, Y. Zhu, and J. Hu, "3D fingerprint recognition based on ridge-valley-guided 3D reconstruction and 3D topology polymer feature extraction," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 43, no. 3, pp. 1085–1091, Mar. 2021.

[16] G. Parziale and Y. Chen, *Advanced Technologies for Touchless Fingerprint Recognition*. Berlin, Germany: Springer, 2009, pp. 83–109.

[17] M. S. Khalil and F. K. Wan, "A review of fingerprint pre-processing using a mobile phone," in *Proc. Int. Conf. Wavelet Anal. Pattern Recognit.*, 2012, pp. 152–157.

[18] R. D. Labati, A. Genovese, V. Piuri, and F. Scotti, "Touchless fingerprint biometrics: A survey on 2D and 3D technologies," *J. Internet Technol.*, vol. 15, no. 3, pp. 325–332, 2014.

[19] R. D. Labati, A. Genovese, V. Piuri, and F. Scotti, *A Scheme for Fingerphoto Recognition in Smartphones*. Berlin, Germany: Springer, 2019, pp. 49–66.

[20] J. Priesnitz, C. Rathgeb, N. Buchmann, C. Busch, and M. Margraf, "An overview of touchless 2D fingerprint recognition," *EURASIP J. Image Video Process.*, vol. 2021, no. 1, pp. 1–28, 2021.
[21] M. O. Derawi, B. Yang, and C. Busch, "Fingerprint recognition with embedded cameras on mobile phones," in *Proc. Int. Conf. Secur. Privacy Mobile Inf. Commun. Syst.*, 2012, pp. 136–147.
[22] C. Stein, C. Nickel, and C. Busch, "Fingerphoto recognition with smartphone cameras," in *Proc. Int. Conf. Biometrics Special Int. Group*, 2012, pp. 1–12.
[23] C. Stein, V. Bouatou, and C. Busch, "Video-based fingerphoto recognition with anti-spoofing techniques with smartphone cameras," in *Proc. Int. Conf. BIOSIG Special Int. Group*, 2013, pp. 1–12.
[24] P. Wasnik, R. Ramachandra, M. Stokkenes, K. Raja, and C. Busch, "Improved fingerphoto verification system using multi-scale second order local structures," in *Proc. Int. Conf. Biometrics Special Int. Group*, 2018, pp. 1–5.
[25] M. Alkhathami, F. Han, and R. V. Schyndel, "A mosaic approach to touchless fingerprint image with multiple views," in *Proc. Int. Conf. Distrib. Smart Cameras*, 2014, pp. 1–8, Art. no. 22.
[26] A. Sankaran, A. Malhotra, A. Mittal, M. Vatsa, and R. Singh, "On smartphone camera based fingerphoto authentication," in *Proc. IEEE Int. Conf. Biometrics Theory, Appl. Syst.*, 2015, pp. 1–7.
[27] L. A. Carney *et al.*, "A multi-finger touchless fingerprinting system: Mobile fingerphoto and legacy database interoperability," in *Proc. Int. Conf. Biomed. Bioinf. Eng.*, 2017, pp. 139–147.
[28] C. Kauba *et al.*, "Towards using police officers' business smartphones for contactless fingerprint acquisition and enabling fingerprint comparison against contact-based datasets," *Sensors*, vol. 21, no. 7, pp. 1–41, 2021.
[29] L. Wang, R. H. Abd El-Maksoud, J. M. Sasian, W. P. Kuhn, K. Gee, and V. S. Valencia, "A novel contactless aliveness-testing (CAT) fingerprint sensor," in *Proc. SPIE*, vol. 7429, 2009, Art. no. 742915.
[30] D. Noh, H. Choi, and J. Kim, "Touchless sensor capturing five fingerprint images by one rotating camera," *Opt. Eng.*, vol. 50, no. 11, pp. 1–12, 2011.
[31] C. Tsai, P. Wang, and J. Yeh, "Compact touchless fingerprint reader based on digital variable-focus liquid lens," in *Proc. SPIE*, vol. 9193, 2014, pp. 173–178.
[32] R. Raghavendra, K. B. Raja, J. Surbiryala, and C. Busch, "A low-cost multimodal biometric sensor to capture finger vein and fingerprint," in *Proc. IEEE Int. Joint Conf. Biometrics*, 2014, pp. 1–7.
[33] A. Weissenfeld, B. Strobl, and F. Daubner, "Contactless finger and face capturing on a secure handheld embedded device," in *Proc. Des., Automat. Test Europe Conf. Exhib.*, 2018, pp. 1321–1326.
[34] A. Genovese, E. Muñoz, V. Piuri, F. Scotti, and G. Sforza, "Towards touchless pore fingerprint biometrics: A neural approach," in *Proc. IEEE Congr. Evol. Comput.*, 2016, pp. 4265–4272.
[35] J. Khodadoust, M. A. Medina-Pérez, R. Monroy, A. M. Khodadoust, and S. S. Mirkamali, "A multibiometric system based on the fusion of fingerprint, finger-vein, and finger-knuckle-print," *Expert Syst. With Appl.*, vol. 176, pp. 1–13, 2021.
[36] X. Pang, Z. Song, and W. Xie, "Extracting valley-ridge lines from point-cloud-based 3D fingerprint models," *IEEE Comput. Graph. Appl.*, vol. 33, no. 4, pp. 73–81, Jul./Aug. 2013.
[37] C. Lin and A. Kumar, "Tetrahedron based fast 3D fingerprint identification using colored LEDs illumination," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 12, pp. 3022–3033, Dec. 2018.
[38] S. Huang *et al.*, "3D fingerprint imaging system based on full-field fringe projection profilometry," *Opt. Lasers Eng.*, vol. 52, pp. 123–130, 2014.
[39] S. Rusinkiewicz, O. Hall-Holt, and M. Levoy, "Real-time 3D model acquisition," *ACM Trans. Graph.*, vol. 21, no. 3, pp. 438–446, 2002.
[40] V. G. Yalla and L. G. Hassebrook, "Very high resolution 3D surface scanning using multi-frequency phase measuring profilometry," in *Proc. SPIE*, vol. 5798, 2005, pp. 44–54.
[41] G. Parziale, E. Diaz-Santana, and R. Hauke, "The Surround Imager™: A multi-camera touchless device to acquire 3D rolled-equivalent fingerprints," in *Proc. Int. Conf. Biometrics*, 2006, pp. 244–250.
[42] R. D. Labati, A. Genovese, V. Piuri, and F. Scotti, "Toward unconstrained fingerprint recognition: A fully touchless 3-D system based on two views on the move," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 46, no. 2, pp. 202–219, Feb. 2016.
[43] W. Xie, Z. Song, and R. C. Chung, "Real-time three-dimensional fingerprint acquisition via a new photometric stereo means," *Opt. Eng.*, vol. 52, no. 10, pp. 1–10, 2013.
[44] R. J. Woodham, "Photometric method for determining surface orientation from multiple images," *Opt. Eng.*, vol. 19, no. 1, 1980, Art. no. 191139.
[45] D. G. Lowe, "Object recognition from local scale-invariant features," in *Proc. IEEE Int. Conf. Comput. Vis.*, 1999, vol. 2, pp. 1150–1157.
[46] C. Sousedik, R. Breithaupt, and C. Busch, "Volumetric fingerprint data analysis using optical coherence tomography," in *Proc. Biometrics Special Int. Group*, 2013, pp. 1–6.
[47] E. Auksorius and A. C. Boccara, "Fast subsurface fingerprint imaging with full-field optical coherence tomography system equipped with a silicon camera," *J. Biomed. Opt.*, vol. 22, no. 9, pp. 1–8, 2017.
[48] H. Tang *et al.*, "3-D ultrasonic fingerprint sensor-on-a-chip," *IEEE J. Solid-State Circuits*, vol. 51, no. 11, pp. 2522–2533, Nov. 2016.
[49] X. Jiang *et al.*, "Monolithic ultrasound fingerprint sensor," *Microsystems Nanoeng.*, vol. 3, pp. 1–8, 2017.
[50] R. G. Maev and F. Severin, "High-speed biometrics ultrasonic system for 3D fingerprint imaging," in *Proc. SPIE*, 2012, vol. 8546, pp. 85–90.
[51] P. Hariharan, *Basics of Interferometry*. Amsterdam, The Netherlands: Elsevier, 2010.
[52] Y. Cheng and K. V. Larin, "Artificial fingerprint recognition by using optical coherence tomography with autocorrelation analysis," *Appl. Opt.*, vol. 45, no. 36, pp. 9238–9245, 2006.
[53] S. Kim, M. Crose, W. J. Eldridge, B. Cox, W. J. Brown, and A. Wax, "Design and implementation of a low-cost, portable OCT system," *Biomed. Opt. Exp.*, vol. 9, no. 3, pp. 1232–1243, 2018.
[54] J. Galbally, L. Beslay, and G. Böstrom, "3D-FLARE: A touchless full-3D fingerprint recognition system based on laser sensing," *IEEE Access*, vol. 8, pp. 145513–145534, 2020, doi: 10.1109/ACCESS.2020.3014796.
[55] D. Maio, D. Maltoni, R. Cappelli, J. L. Wayman, and A. K. Jain, "FVC2002: Second fingerprint verification competition," in *Proc. Int. Conf. Pattern Recognit.*, 2002, vol. 16, pp. 811–814.
[56] H. Ravi and S. K. Sivanath, "A novel method for touch-less finger print authentication," in *Proc. IEEE Int. Conf. Technol. Homeland Secur.*, 2013, pp. 147–153.
[57] X. Liu, M. Pedersen, C. Charrier, F. A. Cheikh, and P. Bours, "An improved 3-step contactless fingerprint image enhancement approach for minutiae detection," in *Proc. Eur. Workshop Vis. Inf. Process.*, 2016, pp. 1–6.
[58] M. Kass and A. Witkin, "Analyzing oriented patterns," *Comput. Vis., Graph., Image Process.*, vol. 37, no. 3, pp. 362–385, 1987.
[59] T. Kamei and M. Mizoguchi, "Image filter design for fingerprint enhancement," in *Proc. Int. Symp. Comput. Vis.*, 1995, pp. 109–114.
[60] S. Chikkerur, A. N. Cartwright, and V. Govindaraju, "Fingerprint enhancement using STFT analysis," *Pattern Recognit.*, vol. 40, no. 1, pp. 198–211, 2007.
[61] Y. Wang, J. Hu, and D. Phillips, "A fingerprint orientation model based on 2D Fourier expansion (FOMFE) and its application to singular-point detection and fingerprint indexing," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 4, pp. 573–585, Apr. 2007.
[62] K. G. Larkin, "Uniform estimation of orientation using local and nonlocal 2-D energy operators," *Opt. Exp.*, vol. 13, no. 20, pp. 8097–8121, 2005.
[63] L. Hong, Y. Wan, and A. Jain, "Fingerprint image enhancement: Algorithm and performance evaluation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 8, pp. 777–789, Aug. 1998.
[64] J. Yang, L. Liu, T. Jiang, and Y. Fan, "A modified Gabor filter design method for fingerprint image enhancement," *Pattern Recognit. Lett.*, vol. 24, no. 12, pp. 1805–1817, 2003.
[65] X. Jiang, "Fingerprint image ridge frequency estimation by higher order spectrum," in *Proc. Int. Conf. Image Process.*, 2000, vol. 1, pp. 462–465.
[66] Z. M. Kovács-Vajna, R. Rovatti, and M. Frazzoni, "Fingerprint ridge distance computation methodologies," *Pattern Recognit.*, vol. 33, no. 1, pp. 69–80, 2000.
[67] L. O. Gorman and J. V. Nickerson, "Matched filter design for fingerprint image enhancement," in *Proc. Int. Conf. Acoust., Speech, Signal Process.*, 1988, vol. 912, pp. 916–919.
[68] L. O'gorman and J. V. Nickerson, "An approach to fingerprint filter design," *Pattern Recognit.*, vol. 22, no. 1, pp. 29–38, 1989.
[69] S. Greenberg, M. Aladjem, D. Kogan, and I. Dimitrov, "Fingerprint image enhancement using filtering techniques," in *Proc. Int. Conf. Pattern Recognit.*, 2000, vol. 3, pp. 322–325.
[70] E. Zhu, J. Yin, and G. Zhang, *Fingerprint Enhancement Using Circular Gabor Filter*, vol. 3212. Berlin, Germany: Springer, 2004, ch. 91, pp. 750–758.

[71] B. G. Sherlock, D. M. Monro, and K. Millard, “Fingerprint enhancement by directional Fourier filtering,” *IEE Proc. - Vis., Image Signal Process.*, vol. 141, no. 2, pp. 87–94, 1994.

[72] C. I. Watson, G. T. Candela, and P. J. Grother, “Comparison of FFT fingerprint filtering methods for neural network classification,” NISTIR, Tech. Rep. 5493, 1994.

[73] S. Jirachaweng and V. Areekul, *Fingerprint Enhancement Based on Discrete Cosine Transform*. Berlin, Germany: Springer, 2007, pp. 96–105.

[74] C. Arcelli and G. S. D. Baja, “A width-independent fast thinning algorithm,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-7, no. 4, pp. 463–474, Jul. 1985.

[75] C. I. Watson *et al.*, “User’s guide to NIST biometric image software (NBIS),” Nat. Inst. Standards Technol., Tech. Rep. 7392, 2007.

[76] V. Piuri and F. Scotti, “Fingerprint biometrics via low-cost sensors and webcams,” in *Proc. IEEE Int. Conf. Biometrics: Theory, Appl. Syst.*, 2008, pp. 1–6.

[77] P. Salum, D. Sandoval, A. Zaghetto, B. Macchiavello, and C. Zaghetto, “Touchless-to-touch fingerprint systems compatibility method,” in *Proc. IEEE Int. Conf. Image Process.*, 2017, pp. 3550–3554.

[78] D. S. Sisodia, T. Vandana, and M. Choudhary, “A conglomerate technique for finger print recognition using phone camera captured images,” in *Proc. IEEE Int. Conf. Power, Control, Signals Instrum. Eng.*, 2017, pp. 2740–2746.

[79] M. Tico and P. Kuosmanen, “Fingerprint matching using an orientation-based minutia descriptor,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 8, pp. 1009–1014, Aug. 2003.

[80] J. Feng, “Combining minutiae descriptors for fingerprint matching,” *Pattern Recognit.*, vol. 41, no. 1, pp. 342–352, 2008.

[81] R. Cappelli, M. Ferrara, and D. Maltoni, “Minutia cylinder-code: A new representation and matching technique for fingerprint recognition,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 12, pp. 2128–2141, Dec. 2010.

[82] W. Yang, J. Hu, and S. Wang, “A Delaunay quadrangle-based fingerprint authentication system with template protection using topology code for local registration and security enhancement,” *IEEE Trans. Inf. Forensics Secur.*, vol. 9, no. 7, pp. 1179–1192, Jul. 2014.

[83] F. Liu, D. Zhang, and L. L. Shen, “Study on novel curvature features for 3D fingerprint recognition,” *Neurocomputing*, vol. 168, pp. 599–608, 2015.

[84] T. N. Ramya and M. B. Veena, “Analysis of polynomial co-efficient based authentication for 3D fingerprints,” in *Proc. IEEE Int. Conf. Innov. Technol.*, 2020, pp. 1–6.

[85] B. Y. Hiew, A. B. J. Teoh, and O. S. Yin, “A secure digital camera based fingerprint verification system,” *J. Vis. Commun. Image Representation*, vol. 21, no. 3, pp. 219–231, 2010.

[86] K. Wang, J. Jiang, Y. Cao, X. Xing, and R. Zhang, “Preprocessing algorithm research of touchless fingerprint feature extraction and matching,” in *Proc. Chin. Conf. Pattern Recognit.*, 2016, pp. 436–450.

[87] R. D. Labati, V. Piuri, and F. Scotti, “A neural-based minutiae pair identification method for touch-less fingerprint images,” in *Proc. IEEE Workshop Comput. Intell. Biometrics Identity Manage.*, 2011, pp. 96–102.

[88] A. K. Jain, S. Prabhakar, L. Hong, and S. Pankanti, “Filterbank-based fingerprint matching,” *IEEE Trans. Image Process.*, vol. 9, no. 5, pp. 846–859, May 2000.

[89] D. G. Lowe, “Distinctive image features from scale-invariant keypoints,” *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, 2004.

[90] K. Tiwari and P. Gupta, “A touch-less fingerphoto recognition system for mobile hand-held devices,” in *Proc. Int. Conf. Biometrics*, 2015, pp. 151–156.

[91] H. Bay, A. Ess, T. Tuytelaars, and L. V. Gool, “Speeded-up robust features (SURF),” *Comput. Vis. Image Understanding*, vol. 110, no. 3, pp. 346–359, 2008.

[92] C. Lee, S. Lee, and J. Kim, *A Study of Touchless Fingerprint Recognition System*, vol. 4109. Berlin, Germany: Springer, 2006, ch. 39, pp. 358–365.

[93] D. Lee, K. Choi, and J. Kim, “A robust fingerprint matching algorithm using local alignment,” in *Proc. Int. Conf. Pattern Recognit.*, 2002, vol. 3, pp. 803–806.

[94] E. Sano *et al.*, “Fingerprint authentication device based on optical characteristics inside a finger,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshop*, 2006, pp. 27–27.

[95] X. Tan and B. Bhanu, “Fingerprint matching by genetic algorithms,” *Pattern Recognit.*, vol. 39, no. 3, pp. 465–477, 2006.

[96] S. Weiguo, G. Howells, M. Fairhurst, and F. Deravi, “A memetic fingerprint matching algorithm,” *IEEE Trans. Inf. Forensics Secur.*, vol. 2, no. 3, pp. 402–412, Sep. 2007.

[97] Q. Zheng, A. Kumar, and G. Pan, “Contactless 3D fingerprint identification without 3D reconstruction,” in *Proc. Int. Workshop Biometrics Forensics*, 2018, pp. 1–6.

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