# A Scheme for Fingerphoto Recognition in Smartphones

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**Abstract** – Touchless fingerprint recognition technologies based on smartphones can be considered selfie biometrics, in which a user captures images of his or her own biometric traits by using the integrated camera in a mobile device (here referred to as selfie fingerprint biometrics). Such systems mitigate the limitations of leaving latent fingerprints, dirt on the acquisition device released by the fingers, and skin deformations induced by touching an acquisition surface associated to a touch ID-based system. Furthermore, the use of the integrated camera to perform biometric acquisition bypass the need of a dedicated fingerprint scanner. With respect to touch-based fingerprint recognition systems, selfie fingerprint biometrics require ad hoc methods for most steps of the recognition process. This is because the images captured using smartphone cameras present more complex backgrounds, lower visibility of the ridges, reflections, perspective distortions, and nonuniform resolutions. Selfie fingerprint biometric methods are usually less accurate than touch-based methods, but their performance can be satisfactory for a wide variety of security applications. This chapter presents a comprehensive literature review of selfie fingerprint biometrics. First, we introduce selfie fingerprint biometrics and touchless fingerprint recognition methods. Second, we describe the technological aspects of the different steps of the recognition process. Third, we analyze and compare the performances of recent methods proposed in the literature.

## 1 Introduction

Smartphones are a type of handheld mobile computer and are widely used all over the world to store sensitive data and to access a wide range of distributed services.

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Therefore, these devices require strong authentication mechanisms for properly managing access to local data and distributed information. For this reason, some recent smartphones possess integrated sets of sensors specifically designed for biometric acquisition, such as fingerprint scanners [17]; illumination systems, optics and cameras for ocular biometrics [39]; and devices for acquiring three-dimensional face samples [1]. In this context, fingerprint-based systems are particularly promising due to their high accuracy and their acceptance by users. However, not all current smartphones include a dedicated fingerprint scanner, whereas almost every smartphone includes a digital camera. Due to recent advances in the speed, resolution, and dynamic range of the digital cameras embedded in smartphones, selfie fingerprint biometrics is attracting increasing interest.[3].

Touchless fingerprint recognition technologies possess important advantages with respect to systems based on traditional touch-based scanners: *i)* the absence of elastic skin deformations, since the finger is not pressed onto any surface; *ii)* the absence of latent fingerprints left on the sensor; *iii)* the absence of dirt on the acquisition surface introduced by the touch-based acquisition process; and *iv)* faster capture of biometric data [16]. However, as shown in Fig. 1, the touchless fingerprint images acquired using the cameras integrated in smartphones can present several nonidealities in comparison to samples acquired using touch-based fingerprint scanners, as follows:

- such an image has a more complex background, including the skin of the finger, instead of containing only the ridge pattern as classical contact-based samples do;
- the illumination is not constant in all regions of the finger in the image;
- the fingerprint image contains reflections, reducing the contrast of the ridge pattern;
- the sample resolution varies because the distance from the finger to the camera is not constant among different acquisitions, thus the application of the most commonly used fingerprint recognition algorithms (designed for samples with a standard resolution of 500 pixels per inch) becomes difficult;
- in many cases, the fingerprint image presents perspective distortions caused by uncontrolled rotations of the finger in three-dimensional space because no pins or references for finger positioning are provided during the acquisition process;
- the ridge pattern may not be sufficiently distinguishable in all regions of the fingerprint due to the limited depth of focus of the optics; and
- the sample may present motion blur.

Due to the aforementioned nonidealities, the accuracy of selfie fingerprint biometrics is currently inferior to that of traditional touch-based technologies [11, 16]. Selfie fingerprint biometric techniques require specifically designed algorithms for most steps of the recognition process.

This chapter is organized as follows. Section 2 describes the biometric recognition process of selfie fingerprint biometrics from a technological point of view, focusing on each step of the computational chain individually. Section 3 presents a

(a) (b)

**Fig. 1** Examples of fingerprint images of the same finger acquired using a touch-based sensor (a) and a smartphone camera (b). The touchless acquisition performed with a smartphone camera presents a more complex background, nonuniform illumination, and out-of-focus regions.

performance analysis of state-of-the-art technologies. Finally, Section 4 concludes the work.

## 2 Biometric recognition process

Several studies in the literature have proposed touchless fingerprint acquisition systems based on a single camera [20, 35], multiple cameras [12, 24, 30, 46], or mobile devices (e.g., smartphone cameras) [4, 5, 42]. Recognition algorithms for touchless fingerprint samples can consider either two-dimensional images or three-dimensional models. While methods based on three-dimensional models can achieve a higher recognition accuracy than methods based on two-dimensional images can, they usually require complex acquisition setups, which are difficult to integrate into smartphones [11].

Selfie fingerprint biometric methods typically consider a single two-dimensional image, which can present the same nonidealities exhibited by touchless samples acquired using any digital camera. For this reason, many existing algorithms can be successfully applied to fingerprint images acquired using smartphone cameras as well as to samples acquired using other touchless devices. In addition, with respect to touchless systems based on a single camera or multiple cameras, mobile devices represent a more compact solution since all hardware and software components necessary to perform a correct acquisition are integrated in a single piece of equipment (e.g., a camera, focus assessment and correction functionalities, an illumination source, and a processing architecture).

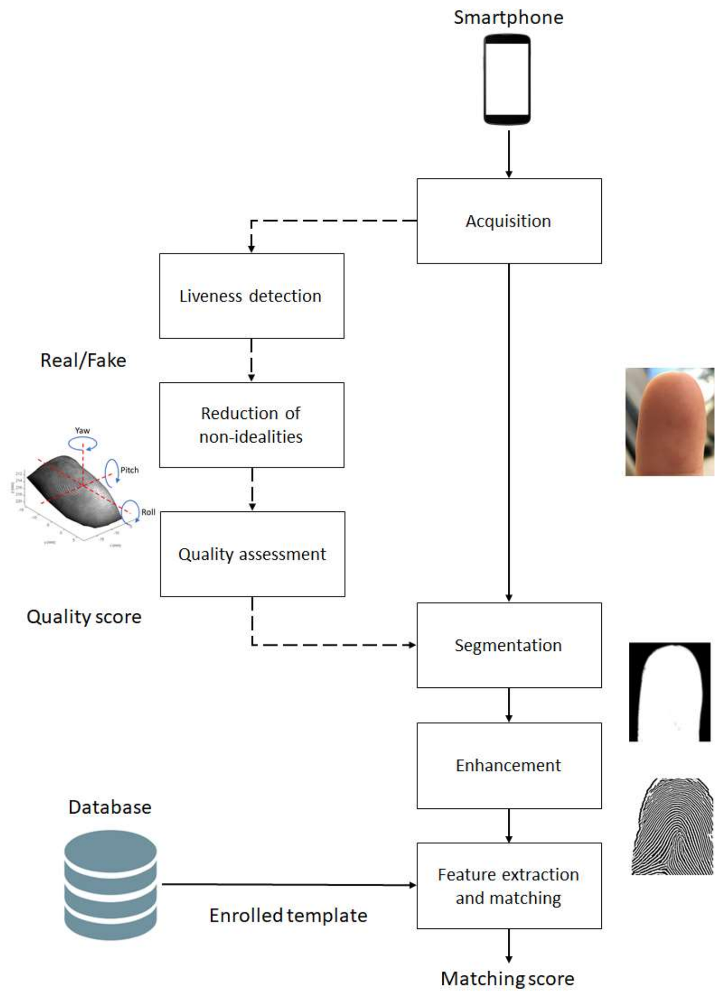


**Fig. 2** Outline of the fingerprint recognition process using images acquired with a smartphone camera.

The recognition procedure in selfie fingerprint biometrics usually consists of four steps: *i)* acquisition, *ii)* segmentation, *iii)* enhancement, and *iv)* feature extraction and matching. In addition, the recognition procedure can also include a quality assessment, a liveness detection, and a step for mitigating the nonidealities of touchless fingerprint sensors. Fig. 2 shows a schema of the recognition process in selfie fingerprint biometrics.

(a) (b)

**Fig. 3** Examples of fingerprint images captured using a smartphone camera under controlled (a) and uncontrolled (b) conditions. In images acquired under controlled conditions, the background is easier to remove, and the ridge pattern is more visible and less affected by noise. However, controlled acquisition setups are less usable than uncontrolled setups are and require a higher level of cooperation from the user.

### *2.1 Acquisition*

During the acquisition process, the biometric trait of interest is presented to the acquisition sensor, and a biometric sample is obtained. In the case of selfie fingerprint biometrics, one or more fingers are presented to the integrated camera of a smartphone, and the collected sample is a two-dimensional image. The acquisition methods presented in the literature feature important differences in terms of the techniques applied to control the finger positioning, illumination and background. Fingerprint images acquired under controlled and uncontrolled conditions present important differences in terms of quality. In particular, acquisition procedures in which the finger positioning, illumination and background are controlled can achieve better-quality images than uncontrolled acquisition techniques. However, controlled acquisition setups require a higher level of cooperation from the user. As an example, Fig. 3 shows fingerprint images of the same finger captured using a smartphone camera under controlled and uncontrolled conditions.

Several acquisition methods based on smartphone cameras are available. In the majority of cases, the camera parameters (focal distance, aperture of the diaphragm, and exposure time) are computed automatically by the acquisition software provided by the operating system, and the operator captures the fingerprint image as soon as the fingertip is within the field of view of the camera. The existing acquisition methods can be classified according to the number of fingers considered and the acquisition constraints applied (in terms of controlled or uncontrolled finger positioning and background). Specifically, it is possible to distinguish five classes: *i)* single fingerprints with controlled finger positioning, controlled background and illumination conditions; *ii)* single fingerprints with uncontrolled finger positioning but controlled background and illumination conditions; *iii)* single fingerprints with uncontrolled finger positioning, uncontrolled background and illumination conditions; *iv)* multiple fingerprints with controlled finger positioning but uncontrolled background and illumination conditions; and *v)* multiple fingerprints with uncontrolled finger positioning, uncontrolled background and illumination conditions.

In acquisition set-ups discussed in class *i)*, images are acquired under laboratory conditions; supports are used to position the smartphone, dedicated illumination setups are used, and the user is required to place his or her finger on a flat surface [6].

In acquisition methods discussed in *ii)*, constraints on the position of the finger are reduced but the background and illumination conditions are controlled [42, 44]. In these setups, the operator (who may also be the owner of the fingerprint) holds the device, while the software installed on the smartphone automatically captures the image. The LED of the smartphone is used as a flashlight to enhance the details of the fingerprint and the contrast with the background, making it easier to segment the region of interest in the image.

In acquisition set-ups discussed in *iii)*, the constraints are further reduced; consequently, such methods must cope with various uncontrolled backgrounds captured under both indoor and outdoor conditions [36]. There are publicly available datasets of fingerprint images captured under both indoor and outdoor conditions with controlled and uncontrolled backgrounds [40, 21].

While most smartphone-based acquisition procedures focus on a single finger at a time, the acquisition methods discussed in *iv)* use multifinger acquisition setups that require previously defined procedures for positioning the fingers [4]. In such an acquisition procedure, a translucent guide is superimposed on the screen of the device to help the user both in correctly positioning the fingers and in capturing images with a constant distance between the fingers and the camera, thereby ensuring a fixed resolution.

The acquisition set-ups discussed in *v)* need to overcome all possible nonidealities of the samples due to an unconstrained acquisition setup. There is a publicly available database of fingerprint samples acquired using smartphones consisting of images collected without any constraints on position, illumination, background, focus, or the number of fingers [22]. These fingerprint images present high variability since they were acquired using different cameras and acquisition software.

## 2.2 Segmentation

The purpose of the segmentation step is to separate the biometric trait of interest from other information in the sample. In the case of selfie fingerprint biometrics, this step aims to extract the region corresponding to the ridge pattern of the last phalanx. The proposed segmentation approaches in the literature can be divided into those based on samples acquired in controlled *i)* or uncontrolled *ii)* backgrounds. While in the first case, it is often possible to use general-purpose segmentation approaches, in the second case, it is necessary to consider additional challenges, such as the properties of the skin color or the presence of out-of-focus regions.

An example of a lightweight method for images acquired with controlled backgrounds is to threshold the red channel of the image to detect the region in which the finger is present [42]. Adaptive thresholding techniques can be applied to color as well as grayscale images [44]; for example, a background subtraction method can be used in combination with a thresholding technique based on the skin color [4].

Segmenting images with uncontrolled backgrounds require methods that are more complex than those based on controlled backgrounds. For example, an algorithmic segmentation approach that consists of a preliminary training step and subsequent refinement steps for background removal is described in [25]. The preliminary training step collects information related to the distribution of the skin pixels in the RGB color space. The first refinement step builds a look-up table using the color distribution information and performs a color-based segmentation to determine whether the pixel belongs to the finger region or not. The second refinement step exploits the frequency information and computes a second segmentation mask by assuming that the regions of the image that do not correspond to the finger are out of focus and therefore contain only limited information at low frequencies. The last step combines the color- and frequency-based results using a region growing algorithm.

Algorithms for skin color detection can also be applied to segment images with uncontrolled backgrounds. A well-known method for skin detection used for segmenting touchless fingerprint images acquired using smartphones is mean shift segmentation. In this method, several segments, each corresponding to a different region of the image, are compared against a fixed reference image to correctly establish which region depicts the finger [23].

Skin detection algorithms may also rely on thresholding channels of the image in color spaces other than the most frequently used RGB color space. Fingerprint segmentation in images acquired using smartphones with uncontrolled backgrounds can be performed by thresholding the magenta (M) channel in the CMYK color space [40] or by thresholding a combination of channels in the YCbCr and HSV color spaces [2].

Recently, deep learning and convolutional neural networks (CNNs) are being increasingly used for a wide variety of signal and image processing applications, including the extraction of relevant information from biometric samples [7]. CNNs can also be successfully applied to segment touchless fingerprint images with uncontrolled backgrounds [5].

In the case of acquisitions with multiple fingers, it is possible either to separate the fingers such that they can be individually matched or to perform multimodal sample-level fusion [37] by treating each multifinger acquisition as a single biometric sample [5]. The separation of different fingers can be performed by estimating the boundaries between the fingers using edge detectors [4].

## 2.3 Enhancement

The enhancement step aims to reduce noise and improve the distinguishability of the distinctive characteristics of a biometric trait. In the case of selfie fingerprint biometrics, the enhancement step is performed in most of the systems and has the purposes of improving the visibility of the ridge pattern and removing unnecessary details in the image. There are two main classes of enhancement techniques applicable to touchless fingerprint images acquired using smartphones: *i)* those that enhance the visibility of the ridges using reduced computational resources and *ii)* schemes that aim to obtain an enhanced representation of the ridge pattern that is as similar as possible to touch-based samples. As an example, Fig. 4 shows a touchless fingerprint image captured with a smartphone camera and the corresponding enhanced representation with minutiae features [33] extracted using a commercial software designed for touch-based samples [34].

Enhancement schemes based on enhancing the visibility of the ridges use well-known image processing algorithms, such as Wiener filtering [36] and adaptive histogram equalization [44] are applied to perform fast computations and enhance the visibility of the ridges.

Schemes aiming to obtain a representation of the ridge pattern similar to touch-based samples are more computationally expensive and usually incorporate two tasks: noise reduction and enhancement of the ridge pattern. The noise reduction task can be performed by applying a median filter [42], followed by histogram equalization [40], and a band-pass filter tuned to the frequency of the ridges [4], or a processing sequence consisting of a Wiener low-pass filter, a top-hat filter, and histogram equalization [31]. The visibility of the ridge pattern can be enhanced by means of an adaptive binarization procedure [42], an unsharp masking algorithm followed by local histogram normalization [40], or a set of Gabor filters tuned according to the local frequency and orientation of the ridges [31].

The proposed schemes may also perform the enhancement step as one single task. As an example, a bank of wavelets can be used to estimate the phase congruency of the frequency response and to extract the local regions of the image with higher phase congruency, which are then identified as parts of the ridge pattern [2].

## 2.4 Feature extraction and matching

The feature extraction step aims to extract a digital representation of unique features from a biometric sample (called a template), while the purpose of matching is to compute a similarity or dissimilarity score between two or more templates (called a matching score or a distance, respectively). In the case of selfie fingerprint biometrics, the methods in the literature can be classified according to the used feature sets: *i)* Level 1 features, *ii)* Level 2 features, and *iii)* learned features. Level 1 features are global characteristics of the ridge pattern [33]. Level 2 features are local characteristics describing certain formations of the ridges, namely, ridge endings or

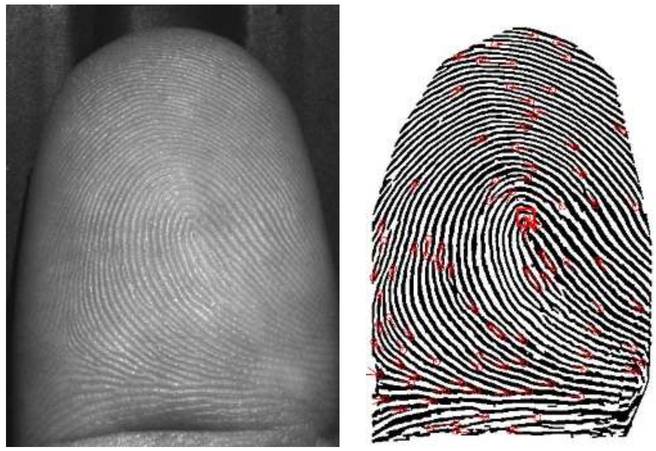

**Fig. 4** Example of a touchless fingerprint image captured with a smartphone camera (a) and the corresponding enhanced representation (b). This figure shows that commercial software [34] can successfully extract the minutiae features [33] from an enhanced touchless fingerprint representation.

bifurcations, also called minutiae [33]. Learned features cannot be classified as pertaining to Level 1 or Level 2 since they are automatically learned from training data; they can be extracted using a variety of computational intelligence techniques, such as artificial neural networks, support vector machines, CNNs, deep neural networks and dictionary-based techniques [18].

Level 1 features are typically designed for touchless fingerprint samples but can also be applied to images acquired using smartphone cameras. There are methods for extracting feature vectors that describe the ridge orientation flow using Gabor filters [19] and methods for extracting singular points from touchless fingerprint samples [8].

Most of the methods in the literature adopt feature extraction and matching techniques pertaining to Level 2. Minutiae-based feature extractors and matchers can be directly applied to touchless fingerprint images acquired using smartphones [6, 27]. However, most of the methods in the literature extract minutiae-based features from enhanced ridge pattern images to achieve better accuracy. To extract and match minutiae-based features, commercial biometric recognition software tools designed for touch-based samples are widely used, with satisfactory results [42, 4, 2]. Furthermore, the minutiae-based feature extractor and matcher included in the Biometric Image Software of the National Institute of Standards and Technology (NIST) [47] can also be applied to enhanced representations of ridge patterns [36]. While not designed for images captured using mobile devices, a minutiae matcher specifically designed for touchless fingerprint images [14] can also be used for fingerprint images acquired using smartphone cameras. Local features other than minutiae points, such as scale-invariant robust features [44], can also be extracted from enhanced representations of ridge patterns.

In recent studies pertaining to learned feature representation, the feature extraction and matching steps have been performed using computational intelligence approaches, with promising results. In particular, it is possible to use scattering networks to extract features and use a random forest classifier to perform the biometric matching [40]. A similar technique using a scattering network and a machine learning classifier is presented in [32]. A competitive coding algorithm and a residual network can also be used in conjunction with a matcher based on the Hamming distance between templates [5].

## 2.5 Quality assessment

In the quality assessment step, a score value is estimated for each image or local region to represent its ability to be processed by the biometric system with satisfactory results. In the case of selfie fingerprint biometrics, quality estimation can be achieved through three main classes of methods, as follows: *i)* estimating the global image quality, *ii)* estimating the quality of local regions, or *iii)* estimating the focus quality for real-time applications. Methods for estimating the global image quality can be used to reject samples with out-of-focus regions or due to low visibility of the ridge pattern due to poor illumination. Methods for estimating the quality of local regions can be used to discard poor-quality regions of a sample during the feature extraction process. Methods for estimating the focus quality can be used to implement autofocusing methods specifically designed for selfie fingerprint biometrics. Fig. 5 shows an example of a fingerprint image in which different regions have different levels of quality.

There are several quality assessment approaches for touchless fingerprint acquisitions pertaining to global image quality estimation. Such methods are typically designed for systems based on either a single camera [13] or multiple cameras [49, 9, 45], but most of them can also be applied to images captured with smartphone cameras. In any case, quality assessment methods trained on images acquired using smartphones can achieve higher accuracy for selfie fingerprint biometrics than methods trained on other types of samples, such as touchless fingerprint images acquired with other kinds of cameras. As an example, the global image quality can be assessed by evaluating the symmetry of the local gradients in the image in combination with a focus estimator [26].

Methods for estimating the local image quality can use sets of features based on the autocorrelation of the fingerprint pattern in the spatial and frequency domains [27] and can also use additional features related to the intensity level of each pixel, the orientation of each local region, and the high-frequency information of the image [28].

Quality assessment methods designed for the real-time selection of correctly focused images are able to run in real time on devices with limited computational power, such as smartphones. For example, a fast and efficient focus estimator analyzes the density and sharpness of the edges in the image [42].

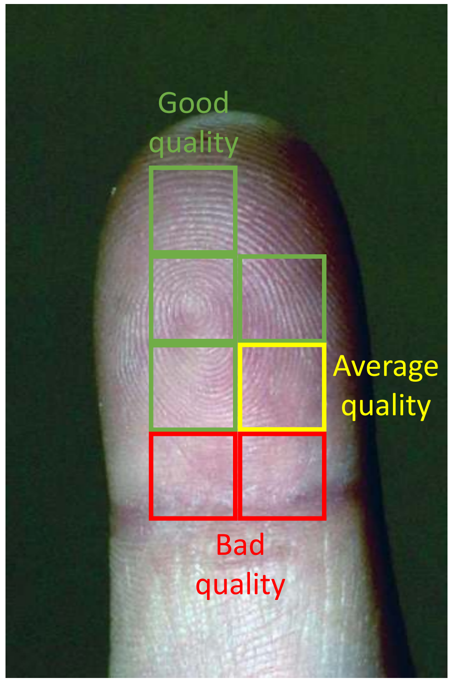


**Fig. 5** Example of the quality assessment of a touchless fingerprint image captured using a smartphone. The figure shows that different regions offer different levels of visibility of the ridge pattern and are therefore associated with different quality values.

## *2.6 Liveness detection*

Liveness detection methods aim to distinguish biometric samples of real biometric traits from possible presentation attacks against the sensor [15]. In the case of selfie fingerprint biometrics, this step aims to distinguish real fingers from synthetic artifacts consisting of heterogeneous materials, printouts, and the images shown on electronic devices. Selfie fingerprint biometrics is a recently emerging research field, and there are only a few studies in the literature on methods for liveness detection that are applicable to touchless samples acquired using smartphones.

It is possible to estimate the presence of a spoofing attack based on frame sequences of fingers. In particular, it is possible to analyze the pattern of the reflection of the material while a finger is gradually moving in front of the camera under the light emitted by the integrated LED of the smartphone and then to estimate the edge density of the fingerprint image [41].

Liveness estimation can also be performed on the basis of a single fingerprint image acquired by a smartphone camera. Various texture descriptors (local binary patterns, dense scale-invariant feature transforms, and locally uniform comparison image descriptors) can be used by a support vector machine to distinguish between real and fake fingerprints [43].

Although some methods have not been tested on images captured using a smartphone, there are liveness detection algorithms based on single touchless fingerprint images that could also be evaluated for images acquired using mobile devices. As an example, the method presented in [48] extracts local binary pattern features and computes gray-level co-occurrence matrices to classify each image as real or fake by means of a feedforward neural network classifier.

### 2.7 Mitigation of nonidealities of touchless fingerprint sensors

This step aims to mitigate the nonidealities of fingerprint images captured with a smartphone (as mentioned in Section 1). Several methods in the literature include an additional processing step with the purpose of mitigating one or more nonidealities of the captured samples. The methods proposed in the literature can be classified according to their goal: *i)* normalizing the fingerprint images to a previously defined resolution, *ii)* reducing perspective distortions due to uncontrolled rotations of the finger during acquisition (Fig. 6), or *iii)* applying surface distortions to increase the compatibility between touchless samples acquired using smartphones and touch-based fingerprint images.

Methods based on normalizing the images aim to mitigate one of the most important nonidealities, namely, the uncontrolled resolution of the fingerprint images due to the absence of pins or references for finger positioning, which help to maintain a constant distance between the finger and the camera among different acquisitions [11]. The resulting nonconstant resolution of the samples prevents the direct use of most of the state-of-the-art minutiae-based fingerprint matching methods, such as the NIST BOZORTH3 software [47], which evaluates the Euclidean distances between pairs of minutiae points. To overcome this problem, studies on touchless fingerprint recognition systems normalize the image resolution to approximately 500 pixels per inch by assuming a constant size for each finger [35]. Other studies have normalized the image resolution by assuming that the ridge frequency is constant for each finger [42]. There are also more complex scaling methods that identify the thick valley between the intermediate phalanges and proximal phalanges for scaling the image accordingly [36].

To alleviate the presence of perspective distortions due to uncontrolled rotations of the finger during acquisition, existing methods estimate the rotations of the finger and apply rigid transformations to each fingerprint sample. In particular, the rotation angles of the finger can be estimated using trained neural networks and then used to compute a frontal view image of the fingerprint by rotating a three-dimensional finger model through the estimated angle [10]. Other approaches estimate finger rotations by evaluating the position of the core point and the contour of the finger [26], or apply a correction to the yaw angle of the finger as estimated from its silhouette [42].

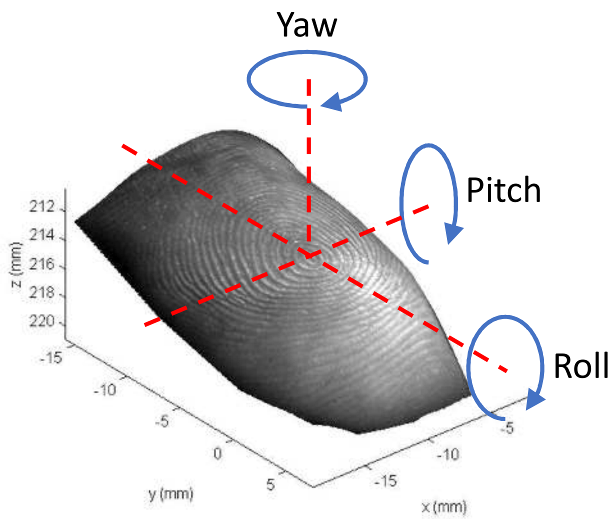


**Fig. 6** The angles of rotation of a finger.

Most methods in the literature pertaining to surface distortions require multi-view acquisition systems [38] or three-dimensional models [11]. Single fingerprint images acquired using smartphone cameras can also be matched with touchless to touch-based fingerprint images using multi-siamese networks [29].

## 3 Performance analysis

Compared to traditional touch-based systems, touchless fingerprint recognition systems based on less-constrained acquisitions usually exhibit a reduction in accuracy [12] because the lower acquisition constraints result in an increase in the distances between samples belonging to the same user. Among touchless fingerprint recognition systems, selfie fingerprint biometric systems often use the least-constrained acquisition procedures, and therefore, such systems currently achieve lower recognition accuracy compared to fingerprint recognition systems based on more-constrained touchless acquisition devices.

Most studies in the literature use private biometric databases collected by the authors. To the best of our knowledge, there are only two publicly available databases of fingerprint images acquired using smartphones:

- The IIITD SmartPhone Fingerphoto Database v1 (ISPFDv1) [21] is composed of 5100 images captured from 128 fingers using an iPhone 5 with autofocus turned on and without any integrated or external illumination source. The images, representing both indoor and outdoor conditions, were collected without the use of

**Table 1** Overview of fingerprint recognition methods using a smartphone camera

| Ref. | DB size (Ind./ Samp.) | Acquisition | Methodology | Accuracy |
|---|---|---|---|---|
| [26] | 60/ 1200 | Single device, indoor acquisition, uniform background, manual focus assessment | Gabor filtering, minutiae extraction and matching algorithms for touch-based samples | EER = 4.12% (single device) |
| [6] | 220 1320 | Multiple devices, indoor acquisition, uniform background, fixed position, controlled illumination | Commercial software for touch-based samples | EER = 4.66% (single device) |
| [42] | 82/ 492 | Multiple devices, indoor acquisition, uniform background | Median filtering, adaptive binarization procedure, commercial software for touch-based samples | EER = 19.1% (multiple devices) |
| [27] | 100/ 2100 | Multiple devices, indoor and outdoor acquisition, unconstrained background | Commercial software for touch-based samples | EER = 16.9% (all samples, multiple devices); EER = 5.81% (high-quality samples, multiple devices) |
| [36] | 100/ 1800 | Multiple devices, indoor and outdoor acquisition, unconstrained background | Wiener filtering, minutiae extraction and matching algorithms for touch-based samples | EER = 3.74% (indoor, single device); EER = 2.04% (outdoor, single device, ≈60% FTA) |
| [44] | 50/ 150 | Single device, indoor acquisition, uniform background | Adaptive histogram equalization, SURF features, nearest neighbors | EER = 3.33% (single device) |
| [40] | 128/ 5100 | Single device, indoor and outdoor acquisition, constrained and unconstrained background | Median filtering, histogram equalization, unsharp masking, scattering network, L1 distance | EER = 3.65% (indoor with outdoor matching, single device) |
| [4] | 33/ 275 | Multiple devices, translucent guide on screen, fixed distance, indoor acquisition, uniform background | Band-pass filter, local histogram normalization, commercial software for touch-based samples | FAR = 0.01% @ FRR = 1% |
| [2] | 1500/ 3000 | Single device, indoor acquisition, unconstrained background | Wavelet filtering, phase congruency, commercial software for touch-based samples | EER = 4.8% (single device) |
| [5] | 230/ 3450 | Multiple devices, indoor and outdoor acquisition, unconstrained background, uncontrolled position and illumination | Competitive coding, CNNs, cosine distance | EER = 35.48% (multiple devices) |

Notes: Ind. = Number of individuals; Samp. = Total number of samples; EER = Equal error rate; FTA = Failure to enroll; FAR = False acceptance rate; FRR = False rejection rate; SURF = Speeded Up Robust Features; CNN = Convolutional neural network.

pins or references for the finger positioning, and have a resolution of 8 megapixels.

- The IIITD Unconstrained Fingerphoto Database (UNFIT) [22] is composed of 3450 images captured from 230 fingers using 45 distinct smartphones and different acquisition software. The images represent both indoor and outdoor conditions, were collected without the use of pins or references for the finger positioning, and have resolutions ranging from 8 to 16 megapixels.

Table 1 presents an overview of the fingerprint recognition methods for images acquired using smartphone cameras, describing the size of the dataset considered, the acquisition procedure, the methodology, and the recognition accuracy. This table shows that current biometric systems based on fingerprint images acquired using smartphones can achieve a satisfactory recognition accuracy for many heterogeneous application scenarios. Furthermore, the results obtained when evaluating methods using sets of images collected under both indoor and outdoor conditions are worse than those achieved when evaluating methods on images collected only under indoor conditions. Similarly, the results obtained for images acquired using multiple different smartphones are inferior to those achieved for images acquired using a single device.

## 4 Conclusions

This chapter presents a review of methodologies for selfie fingerprint biometrics. The existing methods for fingerprint recognition are described, analyzing every step of the biometric recognition process. The performance of the state-of-the-art methods is also compared and analyzed.

State-of-the-art methods enable the acquisition and processing of images of multiple fingerprints with uncontrolled finger positioning and uncontrolled background and illumination conditions. They may use enhancing algorithms and standard minutiae-based recognition techniques or may be based on dedicated feature extractors and matchers. There are also methods for quality estimation, liveness detection, resolution normalization, and the mitigation of perspective distortions as well as techniques for improving the compatibility between touchless and touch-based samples.

Currently, selfie fingerprint biometrics can achieve satisfactory accuracy for a wide variety of identity verification applications. However, these systems are less accurate than traditional touch-based fingerprint recognition technologies. This is because smartphone-based systems use samples acquired under less-constrained conditions, which present additional challenges with respect to touch-based fingerprint images. Furthermore, the results reported in the literature show that there are two main aspects of the acquisition process that contribute to reducing the recognition accuracy: *i)* acquiring images using heterogeneous smartphones and *ii)* performing outdoor acquisition with uncontrolled illumination and background conditions.

To improve the usability of selfie fingerprint biometric techniques, current research trends are oriented towards further lowering the acquisition constraints by considering multi-fingerprint samples acquired in different outdoor scenarios, with uncontrolled backgrounds, illumination conditions, and finger positioning. At the same time, researchers are focusing on improving the recognition accuracy by designing novel enhancement techniques, more efficient feature extraction and matching algorithms such as methods based on deep learning and convolutional neural networks.

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