Touchless Palmprint and Fingerprint Recognition

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Abstract Biometric systems based on hand traits captured using touchless acquisition procedures are increasingly being used for the automatic recognition of individuals due to their favorable trade-off between accuracy and acceptability by users. Among hand traits, palmprint and fingerprints are the most studied modalities because they offer higher recognition accuracy than other hand-based traits such as finger texture, knuckle prints, or hand geometry. For capturing palmprints and fingerprints, touchless and less-constrained acquisition procedures have the advantage of mitigating the problems caused by latent prints, dirty sensors, and skin distortions. However, touchless acquisition systems for palmprints and fingerprints face several challenges caused by the need to capture the hand while it is moving and under varying illumination conditions. Moreover, images captured using touchless acquisition procedures tend to exhibit complex backgrounds, nonuniform reflections, and perspective distortions. Recently, methods such as adaptive filtering, three-dimensional reconstruction, local texture descriptors, and deep learning have been proposed to compensate for the nonidealities of touchless acquisition procedures, thereby increasing the recognition accuracy while maintaining high usability. This chapter presents an overview of the various methods reported in the literature for touchless palmprint and fingerprint recognition, describing the corresponding acquisition methodologies and processing methods.

1 Introduction

Biometric systems based on hand characteristics are widely used in both private and governmental applications. The main reasons for their popularity are their high accuracy, simplicity of use, low cost for hardware devices, compatibility with govern-

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mental and forensic applications, and availability of ad-hoc techniques for protecting the privacy of biometric data [16,36]. The main biometric traits that can be extracted from a hand are the palmprint [56], fingerprints [80], hand geometry [2], finger texture [1], knuckle prints [62], hand veins [124], and finger veins [102]. Among these traits, palmprints and fingerprints are the ones characterized by the most mature technologies and are the most widely used in real-world applications [51].

Traditionally, palmprint and fingerprint recognition systems require the user to touch a sensor platen to acquire a biometric sample. However, the touch-based acquisition process presents several disadvantages:

- the acquired samples can exhibit nonlinear and unpredictable distortions due to the skin deformations induced by touching a surface;
- touching a sensor previously used by unknown persons can present hygiene issues;
- to obtain samples of sufficient quality, users should be trained in the proper way to apply pressure to the acquisition surface; and
- the quality of the acquired samples can deteriorate over time due to the accumulation of grease and dirt released by the hands of users on the sensor platen.

To overcome the mentioned problems and to enhance the usability and acceptability of palmprint- and fingerprint-based biometric systems, the research community has proposed various technological solutions for realizing touchless biometric systems based on cameras placed at a distance from the biometric trait to be captured. The design of such touchless acquisition systems faces several challenges due to the need to capture the hand while it is moving and under varying illumination conditions. Furthermore, touchless samples exhibit relevant differences with respect to those collected through touch-based acquisition. In particular, images captured touchlessly (Fig. 1) tend to exhibit complex backgrounds, nonuniform reflections, and perspective distortions. Therefore, touchless palmprint and fingerprint recognition systems need to adopt different techniques compared with touch-based technologies for all modules of the biometric recognition chain [51].

Touchless palmprint and fingerprint recognition systems can be designed for heterogeneous application contexts, present important differences in their acquisition setups, use two-dimensional (2-D) or three-dimensional (3-D) data, use dedicated preprocessing algorithms, and be based on different feature extraction and matching methods. Their accuracy and robustness have recently increased considerably by virtue of the introduction of deep learning (DL) techniques into every step of the computational chain.

This chapter presents a review of the state of the art in touchless palmprint and fingerprint recognition systems from a technological point of view. Specifically, it describes recent acquisition methods, preprocessing techniques, and feature extraction and matching methods developed for touchless biometric systems based on palmprints and fingerprints. To the best of our knowledge, this is the first literature review providing a systematic analysis of touchless technologies for both palmprint and fingerprint recognition, elucidating their differences and commonalities. While most recent surveys in the literature have focused only on either 2-D or 3-D ap-

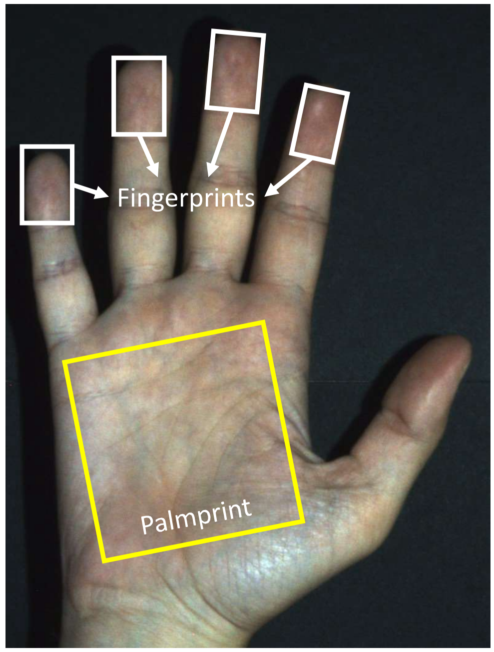

Fig. 1 Positions of the palmprint and fingerprints in a touchless acquisition of a hand.

proaches [24, 30, 94], this work considers both 2-D and 3-D technologies, offering a detailed and comprehensive review.

The chapter is organized as follows. Sec. 2 analyzes touchless palmprint recognition technologies. Sec. 3 reviews touchless fingerprint recognition systems. Sec. 4 concludes the work.

2 Palmprint Recognition

The palm is defined as the region of the palmar side of the hand that extends from the wrist to the base of the fingers (Fig. 1). In this region, the skin covering the hand is of the same type as the skin that covers the fingertips and therefore possesses several distinctive characteristics that enable high-accuracy biometric recognition [38]. Compared to fingerprints, palmprints have the advantages that they can be captured even using low-cost acquisition devices with a low resolution (< 100 dpi), they enable high-accuracy recognition even in the case of damaged hands (e.g., the hands of manual workers or elderly people) since biometric recognition algorithms can exploit features at different levels of detail, and their acquisition is generally well accepted by users, who regard palmprints as less-invasive biometric traits than fingerprints or irises [27, 36, 65, 66, 89].

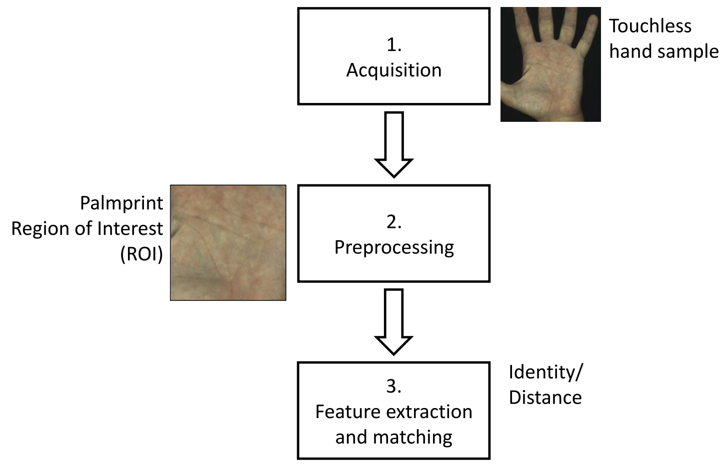

Fig. 2 Outline of the biometric recognition process based on touchless palmprint acquisition.

Because of the high usability and favorable user acceptability commonly associated with palmprint recognition, several recent biometric recognition approaches based on the palm consider the use of touchless and less-constrained acquisition procedures, without the need for a fixed position of the hand or a requirement to touch any surface [3, 38, 55, 64, 85, 134].

In this section, we present the most recent approaches for touchless palmprint recognition, detailing the acquisition procedure, preprocessing algorithms, and methods for biometric feature extraction and matching. Specifically, the recognition procedure of a touchless palmprint recognition system usually consists of the following phases: *i)* acquisition, *ii)* preprocessing, and *iii)* feature extraction and matching. Fig. 2 shows the outline of the recognition process.

2.1 Acquisition

The purpose of the acquisition phase is to capture a 2-D image or 3-D model of the hand in which the details of the palmprint are sufficiently visible to perform biometric recognition (Fig. 3). However, unlike for fingerprints, there is no standard set of features for palmprints, and various acquisition systems have been proposed that capture different types of details at different resolutions. Therefore, there is no standard set of requirements for palmprint acquisition devices. For this reason, most public palmprint databases that are currently available have been captured with different devices and feature high variability in terms of image resolution, dynamic range, and quality [27].

Another drawback of palmprint databases is that the majority of the methods proposed in the literature describe the collection of datasets containing a limited

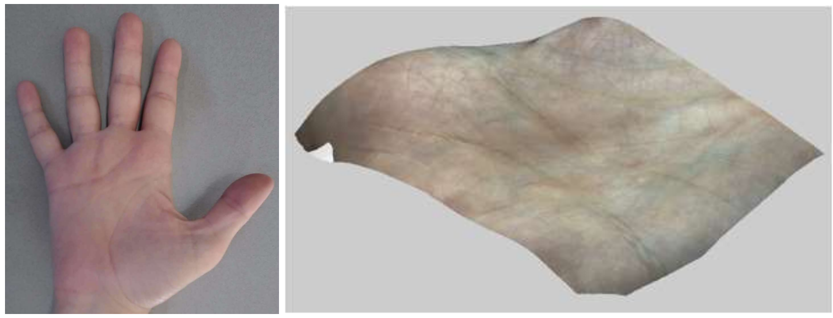

Fig. 3 Examples of touchless palmprint acquisition: (a) a 2-D image captured with an off-the-shelf webcam and a controlled background and (b) a 3-D model computed using a multiple-view acquisition setup. In both cases, although the details of the fingerprints are not visible, the features of the palmprint (e.g., the principal lines) are visible.

number of samples that have not been made public, and therefore, these datasets do not enable the research community to assess the validity of acquisition methodologies by comparing the accuracy of different recognition algorithms [38]. In this section, we do not consider such approaches; instead, to provide the research community with an overview of the most significant acquisition methods in the literature, we consider only the approaches for which a public database has been made available on the internet.

Based on the approaches described in the literature, it is possible to classify the current methods for touchless palmprint acquisition based on the dimensionality of the processed samples. In particular, we can distinguish approaches based on 2-D images from approaches based on 3-D models [38].

2.1.1 Two-Dimensional Approaches

Touchless palmprint recognition methods based on 2-D images use acquisition setups that do not require contact of the palm of the hand with any surface. However, some acquisition systems may use partially constrained setups, in which the back of the hand must be placed against a fixed support. In contrast, other acquisition systems use less-constrained setups that do not require the hand to touch any surface [38]. The acquisition setups used for 2-D touchless palmprint recognition usually include a charge-coupled device (CCD) camera, an enclosure to guide the position of the hand, and an illumination source. Depending on the wavelengths of the illumination used, these acquisition methods can be divided into two categories: *i)* methods based on visible light and *ii)* multispectral methods.

Visible-light acquisition methods include the approach proposed in [47], which describes a touchless acquisition procedure with a controlled background and controlled illumination, in which the user places the back of the hand against a fixed surface inside an enclosure. A method with a similar acquisition procedure is described in [10], which proposes an ad hoc device for capturing the palm of a user while the back of the hand rests on a fixed surface. An enclosure is also used in the approach described in [113]. However, in this case, the hand does not touch any surface, and the enclosure is used only to restrict the placement of the hand inside the field of view and depth of focus of the camera. In contrast to [10, 47, 113], the method described in [8] does not consider either an enclosure or controlled illumination, and proposes a database in which the samples are captured with uncontrolled rotations of the hand. However, the back of the hand is placed against a fixed surface. The method described in [59, 93] considers a similar acquisition procedure used to collect a database from people of different ethnicities, occupations, and ages. While the majority of touchless palmprint databases consider a controlled background, the methods described in [87, 115, 138] are based on a procedure for capturing palmprint samples with uncontrolled backgrounds under visible light using a smartphone. The corresponding samples exhibit high variation in terms of pose, rotation, and distance from the camera. A similar database is described in [82, 86], with the difference that the images are collected from the internet rather than directly captured by the authors.

Multispectral acquisition methods use illuminators at different wavelengths, with the purpose of enhancing different details of the skin. One example is the method described in [9], which relies on a uniform illumination setup composed of six different illuminators ranging from violet to near-infrared wavelengths. In contrast to [9], the approach proposed in [116] involves a simpler acquisition setup, consisting of one visible-light illuminator and one infrared illuminator. The infrared illuminator is obtained by replacing the infrared filter in an off-the-shelf webcam with a visible-light filter.

2.1.2 Three-Dimensional Approaches

Touchless palmprint recognition methods based on 3-D models, similar to those based on 2-D images, use acquisition setups that do not require contact of the palm of the hand with any surface. Their main advantage over methods based on 2-D images is the possibility of reconstructing a 3-D model of the hand that describes the position and orientation of the hand in a 3-D metric space. By using such a 3-D model, it is possible to measure and compensate for variations in the distance and rotation of the hand, which do not need to be fixed, allowing less-constrained acquisition compared with the acquisition setups for 2-D images [21]. Another major advantage is the possibility of using information derived from the 3-D model as additional biometric features, thus increasing the recognition accuracy [30]. However, the acquisition setups for 3-D models are more complex than those for 2-D images since they require devices that are able to determine the position of the hand in 3-D space. More specifically, methods based on 3-D models can be divided into two categories: *i)* methods based on laser scanners and *ii)* approaches using multiple-view acquisitions [38].

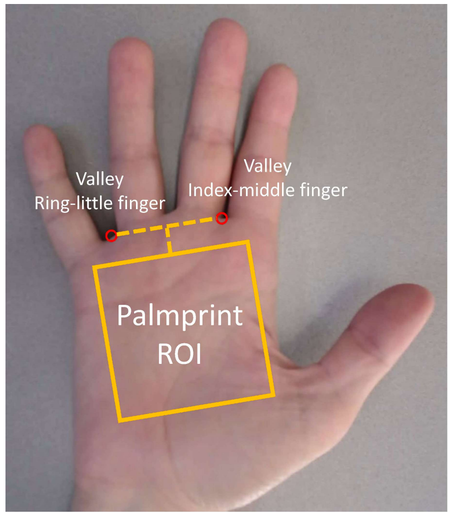

Fig. 4 Example of a hand image, with the extracted valley points, the corresponding reference system, and the resulting region of interest (ROI) of the palmprint.

Methods based on laser scanners include the approach proposed in [55, 110]. In this approach, the reflection of an illumination beam on the surface of the hand is first detected, and triangulation is then applied to determine the position of the hand and reconstruct the 3-D model. The illumination and background conditions are both controlled. The approach described in [54, 111] uses the same acquisition setup described in [55] and additionally introduces a method of increasing the recognition accuracy by compensating for the pose and orientation of the hand at the moment of acquisition.

Approaches using multiple-view acquisition setups include the method proposed in [38][1], which describes a two-view acquisition setup composed only of red-green-blue (RGB) cameras and visible-light illuminators. Notably, while laser scanners enable high-accuracy 3-D reconstruction, the devices are expensive and possibly difficult to obtain. In contrast, the method described in [38] is able to capture two synchronized images of the hand and then reconstruct a 3-D model of the palm using only off-the-shelf components, with a precision sufficient to enable high-accuracy biometric recognition.

2.2 Preprocessing

The purpose of the preprocessing phase is to extract the region of interest (ROI) of the palmprint from a touchless hand sample (Fig. 4). In most methods in the literature,

[1] `https://homes.di.unimi.it/genovese/3dpalm/`

this phase is divided into four steps: *i)* segmentation of the hand, *ii)* extraction of valley points, *iii)* computation of the ROI, and *iv)* enhancement.

The purpose of the hand segmentation step is to remove the background from the captured sample. This step differs depending on whether the background is controlled or uncontrolled. In the case of a controlled background, the majority of palmprint recognition approaches use algorithms based on gray-level thresholding or edge detection, such as the method described in [37]. In the case of an uncontrolled background, most methods in the literature apply segmentation procedures designed to isolate skin-color pixels in an RGB image [43, 63, 84]

The purpose of valley point extraction is to establish a reference system for the subsequent extraction of the ROI, and this step is usually performed by analyzing the local minima of the contour of the segmented hand [14, 84]. For example, in Fig. 4, the ring-little finger valley and the index-middle finger valley are used as reference points to extract the palmprint ROI. However, methods that analyze local minima are robust only for hands with all fingers separated. To compensate for this problem and enable successful valley point extraction in the case of poor separation between fingers, the method proposed in [48] extends the algorithms described in [14, 84] by adding a step based on edge detection.

The aim of ROI computation is to extract a square region capturing the details of the palmprint, and this step is performed by using the extracted valley points to robustly estimate a reference system on the hand (as shown in Fig. 4). Different methods in the literature have considered variants of such reference systems based on the database and the procedure used to extract the features. For example, the procedure described in [3] extracts a rectangular ROI that spans most of the actual palm area by considering the ring-little finger valley and the index-middle finger valley. Recently, methods reported in the literature have been increasingly relying on the use of DL and convolutional neural networks (CNNs) because of their ability to automatically learn data representations by processing the spatial relationships between pixels in an image [40]. In particular, CNNs have been used for the automatic preprocessing of touchless hand images, as in the method described in [82], which extracts the ROI by using a CNN trained on the positions of landmarks.

Finally, palmprint images may be enhanced to increase the visibility of the details used for recognition; however, the enhancement step is seldom performed in the methods reported in the literature, especially with the growing popularity of methods based on machine learning and, in particular, DL. In fact, DL methods based on CNNs can automatically learn a filter structure that can be optimally adapted to each image, as in the approach proposed in [37]. However, the study described in [133] does present an enhancement method for palmprint samples and demonstrates that a particular range of image sharpness levels is correlated with a higher recognition accuracy.

2.3 Feature Extraction and Matching

The purpose of the feature extraction and matching phase is to process the ROI to extract a discriminant representation of the individual and then match the extracted representation to determine the identity associated with the palmprint sample. Traditionally, methods for feature extraction and matching can be divided into line-based, texture-based, subspace-based, coding-based, and local-texture-descriptor-based methods [56]. However, recent approaches are increasingly relying on DL, while line-based, texture-based, and subspace-based approaches are less commonly studied [27, 37]. Therefore, to offer the research community useful insight into the most studied research directions, this chapter will focus on coding-based, local-texture-descriptor-based, and DL-based methods.

2.3.1 Coding-Based Approaches

In methods based on coding, the feature extraction step is performed by first using a set of filters to process the image, quantizing the magnitude or phase of the response for each pixel, and finally encoding the results to compute a biometric template. Then, this template is matched using procedures based on the Hamming distance [38]. Based on the type and number of filters used to process the image, coding-based methods can be divided into three categories: *i)* methods based on a single orientation, *ii)* methods based on multiple orientations, and *iii)* methods based on 3-D shapes. Table 1 presents an overview of such methods.

Methods based on a single orientation encode only one orientation for each pixel in an image. For example, the PalmCode approach [131] uses a single Gabor filter to process the image and then encodes the response for each pixel. Improving on PalmCode, the competitive code method [139] uses several Gabor filters with different orientations to process the image and then, for each pixel, encodes only the index of the filter corresponding to the minimum magnitude response. Such encoding creates a map of the main orientations of the palmprint lines in the image. Similar coding-based methods have subsequently been proposed in the literature to further increase the recognition accuracy by improving the set of filters as well as the coding scheme, such as the double-orientation code [29] and robust line orientation code [53] methods.

Methods based on multiple orientations, in addition to considering the principal orientation of each palmprint line, also consider secondary orientations at each pixel to compute the biometric template. For example, the binary orientation co-occurrence vector approach [41] encodes the responses of all Gabor filters for each pixel. Similarly, for each pixel, the neighboring direction indicator (NDI) method [33] encodes both the principal orientation and the relations with the orientations of neighboring regions. More recently, the robust competitive code approach [127] has been proposed by combining the competitive code algorithm with the NDI approach. Specifically, the robust competitive code method consists of encoding,

Table 1 Summary of coding-based approaches for palmprint recognition

Year	Method	Class	Approach
2003	PalmCode [131]	*i)* Single orientation	Uses a single Gabor filter to process the image, then encodes the magnitude response for each pixel.
2008	Robust line orientation code [53]	*i)* Single orientation	Uses a modified finite Radon transform (MFRAT) to filter the image, encodes the most relevant response for each pixel, and matches encodings based on pixel-to-area comparison.
2010	Competitive code [139]	*i)* Single orientation	Uses multiple Gabor filters with different orientations to filter the image, computes the encoding for each pixel as a number indicating the filter for which the minimum response is obtained, and performs matching using the angular distance.
2016	Double-orientation code [29]	*i)* Single orientation	Uses multiple Gabor filters with different orientations to filter the image, encodes numbers indicating the two most representative filters for each pixel, and then performs matching using the nonlinear angular distance.
2009	Binary orientation co-occurrence vector [41]	*ii)* Multiple orientations	Uses multiple Gabor filters with different orientations to filter the image, then performs encoding for each pixel by considering the responses of all filters.
2016	Neighboring direction indicator [33]	*ii)* Multiple orientations	Uses multiple Gabor filters with different orientations to filter the image, then computes the encoding for each pixel by considering both the orientation of the most relevant filter and the relations with the orientations in adjacent regions.
2018	Robust competitive code [127]	*ii)* Multiple orientations	Uses multiple Gabor filters with different orientations to filter the image, encodes the representation by considering the orientation of the filter with the most relevant response as well as the weighted responses for adjacent regions, and then matches the representation using the angular distance.
2011	SurfaceCode [55]	*iii)* 3-D shape	Applies surface interpolation to local areas, computes a shape index for each pixel, and encodes the results using 4 bits for each pixel.

for each pixel, the most relevant orientation and a weighted combination of the orientations in adjacent regions.

Methods based on 3-D shapes encode the 3-D shape of a palmprint. For example, the SurfaceCode approach [55] applies surface interpolation to the point cloud obtained using a laser scanner; then, for each pixel, it computes a shape index describing the local 3-D model and encodes the result using 4 bits.

2.3.2 Local-Texture-Descriptor-Based Approaches

Recent methods for touchless palmprint recognition have widely considered local texture descriptors since they have been proven to be robust to local variations in rotation, translation, scale, and illumination [12, 129], which are more likely to be present in touchless samples than in samples captured using a touch-based procedure [37]. Therefore, methods based on local texture descriptors are better suited than coding-based methods for achieving high-accuracy recognition based on palmprint samples captured using touchless acquisition procedures [27]. Specifically, recent approaches for touchless palmprint recognition based on local texture descriptors involve computing, for each local region of the ROI image, a blockwise histogram describing the orientations of the lines on the palm [67, 77, 134]. Then, a biometric template is computed by concatenating all of these blockwise histograms, thereby obtaining a global feature descriptor for the whole image. Finally, various distance measures (e.g., the Euclidean or chi-squared distance) are used to compare different templates generated in this way [5]. Approaches based on local texture descriptors can be divided into three categories: *i)* methods using general-purpose descriptors applied to palmprint images, *ii)* methods using texture descriptors encoding the main orientation for each pixel, and *iii)* methods using texture descriptors encoding multiple orientations for each pixel. Table 2 presents an overview of such methods.

Methods using general-purpose descriptors consider local texture descriptors that have been previously proposed in the literature and apply them for touchless palmprint recognition, such as the local binary patterns (LBP) descriptor [119], the scale-invariant feature transform (SIFT) [125], the local directional patterns (LDP) descriptor [28], the histograms of oriented gradients (HOG) descriptor [52], and the local tetra patterns (LTrP) descriptor [67].

Methods using texture descriptors encoding the main orientation for each pixel, in contrast to methods using general-purpose descriptors, rely on local texture descriptors designed especially for palmprint recognition, such as the histograms of oriented lines (HOL) descriptor [52], which is a variant of the HOG descriptor based on Gabor filters, or the modified finite Radon transform (MFRAT), to better enhance the palmprint lines. Similarly, the collaborative representation competitive code (CR-CompCode) method [134] is a modification of the competitive code approach [139] in which a technique of computing a template based on blockwise histograms is introduced and then a sparse representation classifier [135] is used to compare templates.

Methods using texture descriptors encoding multiple orientations for each pixel, in contrast to methods that encode a single orientation for each pixel, consider a feature descriptor that encodes multiple orientations. For example, the local line directional patterns (LLDP) descriptor [77] is an extension of the LDP descriptor [50] that computes the line responses at each pixel using several Gabor filters with different orientations or the MFRAT. Then, both the minimum and maximum responses are encoded for each pixel, the corresponding blockwise histograms are calculated, and a distance measure is used to compare the resulting templates. Improving on the LLDP descriptor, the local multiple directional patterns (LMDP) descriptor [28] considers multiple dominant directions for each pixel, the confidence associated with each direction, and the relations with directions in adjacent regions. Similarly, the discriminant direction binary code (DDBC) [31] considers different directions by using a filter-based approach to compute the convolution differences between neighboring directions and then learns a feature mapping to project the convolution results into a feature vector. To further improve the accuracy by gaining insight into which directions are the most representative, the local discriminant direction binary

Table 2 Summary of local-texture-descriptor-based approaches for palmprint recognition

Year	Method	Class	Approach
2014	SIFT [125]	*i)* General purpose	Combines the scale-invariant feature transform (SIFT) for feature extraction with random sample consensus (RANSAC) for filtering outliers.
2006	LBP [119]	*i)* General purpose	Uses the local binary patterns (LBP) descriptor to compute a template, then performs matching using an AdaBoost classifier.
2014	HOG [52]	*i)* General purpose	Uses the histograms of oriented gradients (HOG) descriptor to compute a template.
2016	LDP [28]	*i)* General purpose	Applies the local directional patterns (LDP) descriptor to compute a template, then matches the template using the chi-square distance.
2017	LTrP [67]	*i)* General purpose	Uses the local tetra patterns (LTrP) descriptor to compute a template.
2014	HOL [52]	*ii)* Texture descriptors encoding the main orientation	Uses a variant of the HOG descriptor to preprocess the input image by applying either Gabor filters or the MFRAT.
2017	CR-CompCode [134]	*ii)* Texture descriptors encoding the main orientation	Uses a combination of competitive code with block-wise histograms to compute a template, then performs matching using a sparse representation classifier.
2016	LLDP [77]	*iii)* Texture descriptors encoding multiple orientations	Computes the most relevant orientation for each pixel by using either Gabor filters or the MFRAT, creates a template by encoding the corresponding responses, and then performs matching using either the Manhattan distance or the chi-square distance.
2016	LMDP [28]	*iii)* Texture descriptors encoding multiple orientations	Uses an encoding scheme that considers multiple relevant orientations for each pixel as well as their confidence and the relations with neighboring regions.
2017	LMTrP [67]	*iii)* Texture descriptors encoding multiple orientations	Computes the most relevant orientation for each pixel by using either Gabor filters or the MFRAT, then extracts the derivatives at each pixel in both the horizontal and vertical directions while also considering adjacent pixels to account for the thickness of the lines.
2019	DDBC [31]	*iii)* Texture descriptors encoding multiple orientations	Uses a filter-based approach to compute local convolutions for different directions, then learns a feature mapping to extract a feature vector.
2020	LDDBP [32]	*iii)* Texture descriptors encoding multiple orientations	Applies a method based on a combination of LBP and an analysis of the most discriminative directions for each pixel.

pattern (LDDBP) approach [32] is based on an analysis of the discriminative power of each different direction in combination with the LBP descriptor. In contrast to the majority of the methods of class *iii)*, which achieve increased accuracy by encoding the most representative orientations, the local microstructure tetra patterns (LMTrP) descriptor [67] improves the recognition accuracy by considering the line thickness at each pixel in addition to describing the different local orientations.

Table 3 Summary of DL-based approaches for palmprint recognition

Year	Method	Class	Approach
2018	AlexNet, VGG-16, VGG-19 [109]	*i)* Pretrained CNNs	Uses pretrained CNNs to extract features, then classifies them using a support vector machine (SVM).
2018	AlexNet [97]	*i)* Pretrained CNNs	Uses pretrained CNNs to extract features, then classifies the feature vectors using an SVM.
2016	AlexNet, discriminative index learning [106]	*ii)* CNNs fine-tuned on palmprint images	Uses a CNN based on the AlexNet architecture, trained using a loss function that considers the separation between genuine and impostor distributions.
2020	C-LMCL [137]	*ii)* CNNs fine-tuned on palmprint images	Uses a CNN based on the ResNet architecture, with a loss function designed for uniformly clustering feature vectors of different classes.
2020	GoogLeNet, adversarial metric learning [138]	*ii)* CNNs fine-tuned on palmprint images	Uses a CNN based on the GoogLeNet architecture, trained using a technique based on adversarial metric learning.
2020	EE-PRNet [82]	*ii)* CNNs fine-tuned on palmprint images	Uses a CNN trained to segment and classify palmprint images using an end-to-end learning algorithm.
2017	PCANet [83]	*iii)* CNNs trained on palmprint images	Uses a CNN in which the filters are learned using an unsupervised procedure based on principal component analysis (PCA).
2019	PalmNet [37]	*iii)* CNNs trained on palmprint images	Uses a CNN in which the filters are learned and adapted to the database using an unsupervised procedure based on Gabor analysis and PCA.
2019	FusionNet [39]	*iii)* CNNs trained on palmprint images	Uses PCANet for the fusion of palmprint and inner finger texture features.

2.3.3 Deep-Learning-Based Approaches

Currently, the majority of approaches for pattern recognition, including biometric systems, consider techniques based on DL and CNNs [105]. Approaches using CNNs are capable of extracting knowledge from data affected by noise, such as perspective distortions and local changes in rotation, translation, and scale, which are typical of biometric samples captured using touchless or less-constrained procedures [15, 19]. Moreover, CNNs can adapt to samples captured in heterogeneous environments [18]. Because of the advantages of DL for biometric recognition, several approaches in the literature consider CNNs for touchless and less-constrained palmprint recognition [37, 82, 83, 97, 106]. These approaches usually involve applying a CNN to ROI images to extract discriminative features and then computing a distance measure to compare the resulting templates. DL-based approaches for touchless palmprint recognition can be divided into three categories: *i)* methods using pretrained CNNs, *ii)* methods using CNNs fine-tuned on palmprint images, and *iii)* methods using CNNs trained on palmprint images. Table 3 presents an overview of such methods.

Methods using pretrained CNNs extract features from palmprint images using CNNs previously trained on a general-purpose dataset, such as the method introduced in [109], which compares the results obtained using AlexNet [57], VGG-16, and

VGG-19 [103]. Then, this method uses a support vector machine (SVM) to perform classification. A similar procedure is described in [97] for recognizing the palmprints of newborns as captured using a touchless acquisition procedure.

Methods using CNNs fine-tuned on palmprint images also rely on pretrained CNNs, but only after these CNNs have been fine-tuned on palmprint images. Such methods adapt the pretrained neural models to palmprint samples and can achieve a greater recognition accuracy than methods using only pretrained CNNs. For example, the work proposed in [106] starts from a CNN architecture based on the AlexNet model and then trains the CNN using a loss function based on the separation between genuine and impostor scores. Similarly, the centralized large margin cosine loss (C-LMCL) method proposed in [137] uses a CNN based on the ResNet architecture [44] and introduces a loss function designed to uniformly cluster classes in the feature space by separating the feature vectors of different individuals while ensuring that the feature vectors of the same individual remain close to each other. The work described in [138] extends this concept by introducing a CNN based on the GoogLeNet architecture [107], trained using a technique based on adversarial metric learning, with the purpose of further improving the division of templates in the feature space in accordance with their classes. Rather than using segmented ROIs, the work proposed in [82] describes EE-PRNet, a CNN based on the VGG-16 architecture fine-tuned to directly process touchless hand images, extract the palmprint ROI, and then perform individual classification.

Methods using CNNs trained on palmprint images rely on training CNNs from scratch on palmprint images. In particular, the approach described in [83] considers PCANet [7], a CNN trained using an unsupervised procedure based on principal component analysis (PCA). This method uses PCANet to extract a feature vector from the palmprint ROI and then classifies the resulting template using an SVM. Similarly, PalmNet[2], proposed in [37], is a CNN in which the filters are learned using an unsupervised procedure based on Gabor analysis and PCA. Gabor analysis is performed to preliminarily select the Gabor filters that are best adapted to the palmprint images based on the palm size, rotation, and scale. The filters are then further adapted to the images using a PCA-based procedure. PCANet is also used in FusionNet[3] [39], which fuses the feature vectors obtained by applying PCANet to both palmprint and inner finger texture image regions.

3 Fingerprint Recognition

Fingerprints are reproductions of the surface pattern of the fingertip epidermis. This pattern is a characteristic sequence of interleaved ridges and valleys, usually considered unique for each individual. Biometric systems based on touchless fingerprint samples attempt to perform recognition by extracting and processing the

[2] http://iebil.di.unimi.it/palmnet/index.htm

[3] http://iebil.di.unimi.it/fusionnet/index.htm

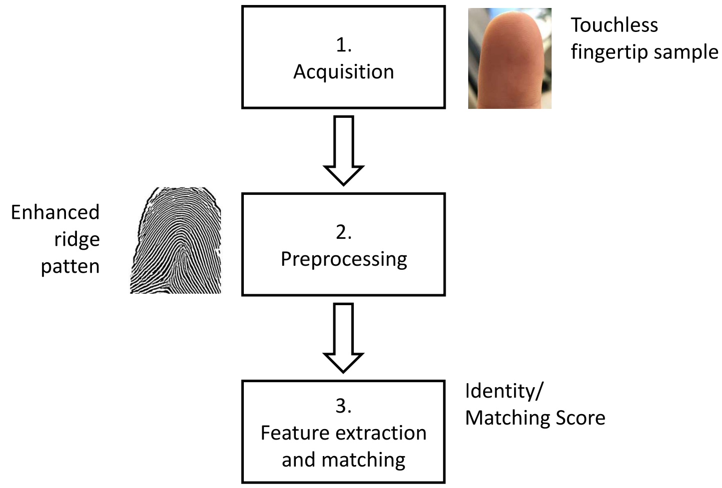

Fig. 5 Outline of the biometric recognition process based on touchless fingerprint acquisition.

discriminative information present in traditional fingerprint images from touchless finger images [94] or 3-D models acquired using touchless technologies [22, 26]. Compared with palmprints, fingerprints offer the following advantages: users are frequently more familiar with this biometric recognition approach since fingerprint recognition systems are the most mature and widely used biometric technologies [80], and touchless fingerprint recognition technologies can produce templates compatible with existing governmental and investigative databases, such as those adopted in the Automated Fingerprint Identification System [81].

With the aim of designing systems that are more usable and acceptable than traditional touch-based technologies for fingerprint recognition, several recent studies have focused on touchless and less-constrained acquisition procedures, which can be based on either the integrated cameras in mobile devices [24] or dedicated acquisition systems [58].

In this section, we present the most recent approaches for touchless fingerprint recognition, describing state-of-the-art methods designed for every step of the biometric recognition process. The recognition procedure of a touchless fingerprint recognition system usually consists of the following phases: *i)* acquisition, *ii)* preprocessing, and *iii)* feature extraction and matching. Fig. 5 shows the outline of the recognition process.

3.1 Acquisition

The purpose of the acquisition phase is acquire an image, a 3-D model of the last finger phalanx, or a 3-D model of the ridge pattern with sufficient distinguishability

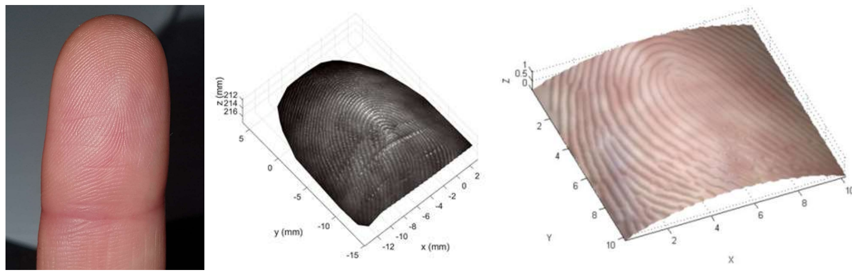

Fig. 6 Examples of touchless fingerprint acquisition: a) a single image acquired using a smartphone with uncontrolled background and illumination conditions, b) a 3-D model of the finger shape, and c) a 3-D model of the ridge pattern.

of the distinctive characteristics to allow biometric recognition to be performed (Fig. 6).

The approaches proposed in the literature for acquiring touchless fingerprint samples exhibit important differences in terms of finger placement guides, the number of cameras, illumination techniques, and the use of either uniform or uncontrolled backgrounds. Therefore, there is no standard approach, and the types of acquisition constraints imposed depend on the application scenario for which the biometric system has been designed.

In the following, we divide state-of-the-art touchless fingerprint acquisition techniques into approaches based on 2-D images and approaches based on 3-D models [26].

3.1.1 Two-Dimensional Approaches

The state-of-the-art approaches designed for the acquisition of 2-D samples can be divided into three main groups: *i)* methods for acquiring a single image using a frontal illumination source, *ii)* approaches designed to compensate for the nonidealities of single touchless images using hardware solutions, and *iii)* multimodal acquisition approaches.

Methods for acquiring a single image using a frontal illumination source are the most common ones. They can be based on heterogeneous kinds of cameras, such as the integrated cameras in smartphones [24], webcams [92], cameras designed for industrial applications [23], and consumer cameras [39]. Various constraints may also be imposed during the acquisition process depending on the scenario for which the biometric system is designed. Depending on the acquisition constraints, the following classes of acquisition setups can be distinguished: *a)* setups for collecting single fingerprints with controlled finger positioning as well as controlled background and illumination conditions [17], *b)* setups for collecting single fingerprints with uncontrolled finger positioning but controlled background and illumination conditions [112], *c)* setups for collecting single fingerprints with uncontrolled finger positioning as well as uncontrolled background and illumination conditions [96], *d)* setups for collecting multiple fingerprints with controlled finger positioning but uncontrolled background and illumination conditions [46], and *e)* setups for collecting multiple fingerprints with uncontrolled finger positioning as well as uncontrolled background and illumination conditions [13].

Approaches designed to compensate for the nonidealities of single touchless images using hardware solutions are based on more complex and expensive acquisition setups than methods for acquiring a single image using a frontal illumination source. The approaches pertaining to this class can be divided into methods of compensating for perspective rotations, increasing the depth of field, and mitigating the detrimental effects of damaged finger skin. To compensate for perspective rotations, some studies have investigated capture devices capable of acquiring the nail-to-nail finger surface by means of rotating line scan cameras [90]. Other approaches rely on capturing multiple images from different viewpoints to compute a fingerprint image representing the complete ridge pattern by means of image stitching techniques [11]. To increase the depth of field of traditional cameras and thus enhance the ability of biometric systems to process fingerprint images acquired from nonfrontal positions, some studies have investigated the use of digital variable-focus liquid lenses [114]. To mitigate the detrimental effects of damaged finger skin, some systems are able to capture ridge patterns in the internal layers of the finger by using a red-light illumination source placed against the back of the fingernail [100].

Multimodal acquisition approaches are designed to acquire heterogeneous biometric traits using a single hardware device. For example, there are methods for simultaneously acquiring fingerprints and finger vein patterns [90, 118] as well as handheld embedded devices that can capture multiple touchless fingerprints and face images [123].

3.1.2 Three-Dimensional Approaches

The advantage of 3-D acquisition systems compared with 2-D acquisition systems is that they can capture additional information, thereby overcoming some of the problems related to perspective distortions, providing additional data for processing, and enhancing the compatibility between touchless and touch-based technologies. However, 3-D acquisition systems also require more complex and expensive hardware than 2-D acquisition technologies.

Systems for 3-D fingerprint acquisition can be divided into two classes: *i)* systems that acquire models describing the 3D shape of the finger and *ii)* systems that acquire models describing the 3-D characteristics of the ridge pattern.

Systems that acquire models describing the 3D shape of the finger are usually based on multiple-view acquisition setups and use multiple images acquired from different viewpoints to compute the 3-D coordinates of corresponding points in the images by applying the triangulation principle. Most of these methods require the use of guides for finger placement to control the orientation of the finger in 3-D space [74, 91]. However, there are also methods that are able to acquire 3-D samples on the move, without any guide for finger placement [23]. The 3-D reconstruction process requires a search for corresponding pairs of points in the images, which can be performed using correlation-based strategies [23] or methods of computing denser representations by using more complex feature sets [73, 75].

Systems that acquire models describing the 3-D characteristics of the ridge pattern have the advantage of collecting additional information that can be used for feature extraction and matching. However, they usually acquire multiple frames over time and thus require the use of finger placement guides to keep the finger still for the required acquisition time. Systems that acquire models describing the 3-D characteristics of the ridge pattern can be based on various techniques: photometric stereo 3-D reconstruction, ultrasonic sensors, structured light imaging, or laser sensing. Systems based on photometric stereo 3-D reconstruction capture multiple images under variable lighting conditions from a fixed viewpoint [70, 126, 136]. Such a reconstruction system assumes that the finger is illuminated only by the light sources of the sensor itself. Ultrasonic sensors may be used to acquire either 3-D or 2-D models of the internal skin layers [49]. Technologies for 3-D fingerprint acquisition based on ultrasonic sensors are currently in the prototype stage [78, 98], and there are not yet any studies on complete biometric recognition systems based on this technology. Systems based on structured light imaging project successive light patterns of different frequencies onto the finger. A fixed camera is used to acquire a set of images, which are then processed to estimate the shape of each single pattern and compute the distance of every point in the field to determine its deformation with respect to the original pattern [72, 120, 121]. Laser sensing permits accurate 3-D reconstruction with limited processing resources. As an example, the 3-D fingerprint reconstruction systems presented in [34, 35] use a laser line scanner to estimate the depth of the ridges.

3.2 Preprocessing

The touchless fingerprint recognition systems reported in the literature exhibit important differences in the preprocessing phase, which can be due to the acquisition techniques used or to the application scenario for which a system has been designed. Nevertheless, it is possible to distinguish six main computational tasks: *i)* segmentation, *ii)* texture enhancement, *iii)* 3-D model enhancement, *iv)* resolution normalization, *v)* compensation of perspective deformations, and *vi)* mapping of 3-D models to 2-D images.

The purpose of segmenting a touchless fingerprint sample is to remove the background and select an ROI corresponding to the last phalanx of a single finger. The segmentation methods presented in the literature differ depending on whether the acquisition system uses a fixed or uncontrolled background. In the first case, it is often possible to use general-purpose segmentation approaches, such as thresholding techniques [112] or background subtraction [6]. In the second case, segmenting the finger region is a more challenging task and requires more complex techniques, such as skin detection algorithms [4, 99] or methods based on CNNs [68, 79]. In the case of acquisitions of multiple fingers, the segmentation task requires separating every finger, frequently using image processing algorithms based on edge detectors [13].

The purpose of texture enhancement is to reduce noise and improve the distinguishability of the distinctive characteristics of the ridge pattern. This task can be performed by both 2-D and 3-D touchless fingerprint recognition systems that acquire samples using CCD cameras. The enhancement techniques for touchless fingerprint images can be divided into two classes: algorithms that enhance the visibility of the ridges using reduced computational resources and methods that compute an enhanced representation of the ridge pattern similar to those obtained from touch-based images. Techniques of the first class usually increase the contrast between ridges and valleys using algorithms such as Wiener filtering [96] and adaptive histogram equalization [112]. Techniques of the second class are more computationally expensive and usually consist of a noise reduction algorithm and a method for enhancing the ridge pattern [76,99,104]. Some methods for computing ridge pattern images similar to touch-based samples can also be performed in a single computational step, for example, using a bank of wavelets [4].

The purpose of 3-D model enhancement is to reduce the presence of noise and outliers. Systems designed to reconstruct the 3-D finger shape frequently refine the computed point clouds by applying techniques for approximating the finger shape as a 3-D surface. Some techniques approximate the finger shape as a previously defined shape [74]. Other methods perform noise reduction by approximating the finger shape using thin plate splines [23]. Recent studies have obtained remarkable results using binary quadratic functions [132]. Systems designed to reconstruct the 3-D ridge pattern adopt fewer assumptions on the finger shape, and the preprocessing phase frequently consists of the application of frequency filters [120].

Resolution normalization may be necessary to enable accurate biometric recognition since most state-of-the-art matchers require samples of fixed resolution. In touchless fingerprint recognition systems based on 3-D models and in systems based on 2-D samples that impose a fixed placement of the finger, the sample resolution is known a priori. In contrast, 2-D touchless systems that do not impose any constraint on finger placement frequently need to estimate and normalize the image resolution. This task can be performed by imposing a constant size for each finger [92], assuming that the ridge frequency is constant for each finger [104], or identifying the thick valley between the intermediate phalanges and proximal phalanges to estimate the finger size [96].

The aim of compensating for perspective deformations is to mitigate the detrimental effects of 3-D rotations of the finger samples. Methods in the literature estimate the finger pose from a single touchless fingerprint image [21,104,130] and subsequently apply compensation techniques based on synthetic 3-D models approximating the finger shape [21,108].

Methods for mapping 3-D models to 2-D images attempt to enhance the compatibility between 3-D touchless fingerprint recognition systems and touch-based technologies. The mapping process may consist of unwrapping the 3-D models to obtain 2-D images similar to rolled fingerprints [42,42,95,101,120,121] or may use geometrical models to compensate for both the perspective deformations of touchless samples and the nonlinear deformations introduced by touching an acquisition surface [69]. Unwrapping approaches can be further classified into parametric and nonparametric methods. Parametric methods use geometrical shapes that are known a priori to approximate the finger shape. They can convert the coordinates of a fingerprint into cylindrical coordinates [42], apply local conversions in polar coordinates by using sets of rings [120], or perform conversion into cylindrical coordinates followed by a refinement algorithm [121]. Nonparametric methods use more complex techniques that aim to preserve the distances between distinctive points of the ridge pattern. They can be based on various heuristics [42, 101] and include algorithms intended to enhance the compatibility with touch-based fingerprint databases by simulating the pressure of the finger on the acquisition sensor [95].

3.3 Feature Extraction and Matching

The goal of the feature extraction and matching phase is to extract distinctive characteristics from the fingerprint samples and compute the result of the recognition process. Most touch-based fingerprint recognition systems are based on minutiae features and are designed for identity verification [80]. Similarly, most studies on touchless fingerprint recognition rely on minutiae points. There also exist methods based on different features as well as machine learning approaches and DL strategies.

3.3.1 Minutiae-Based Approaches

The minutiae are distinctive points of the ridge pattern corresponding to bifurcations and terminations of the ridges [80]. Feature extraction and matching approaches based on minutiae features can be divided into three classes: *i)* methods designed for touch-based samples, *ii)* methods designed for 2-D touchless samples, and *iii)* methods designed for 3-D touchless samples. Table 4 presents an overview of such methods.

Methods designed for touch-based samples are the most commonly used approaches in touchless fingerprint recognition systems based on both 2-D and 3-D samples. Specifically, many touchless systems adopt commercial feature extractors and matchers designed for touch-based samples [88], achieving impressive accuracy [104]. Open-source libraries designed for touch-based samples, such as the National Institute of Standards and Technology Biometric Image Software (NIST NBIS) [122], can also achieve satisfactory performance [20] when applied to enhanced representations of ridge patterns obtained from touchless images.

Methods designed for 2-D touchless samples attempt to overcome the nonidealities specific to touchless fingerprint images. Some minutiae extractors for touchless samples have been designed based on DL strategies [108]. Furthermore, minutiae matchers designed for touchless fingerprint images have been reported based on genetic algorithms [128] and artificial neural networks [25].

Table 4 Summary of minutiae-based approaches for fingerprint recognition

Year	Method	Class	Approach
Since 1998	Neurotechnology VeriFinger [88]	*i)* Methods designed for touch-based samples	Is the most widely used software development kit for feature extraction and matching of touchless fingerprint samples (commercial software).
2007	NIST NBIS [122]	*i)* Methods designed for touch-based samples	Is a software development kit that can achieve satisfactory performance when applied to enhanced representations of ridge patterns obtained from touchless images (open-source software).
2020	Deep minutiae [108]	*ii)* Methods designed for 2-D touchless samples	Uses a 3-D-based method to compensate for perspective distortions, applies a deep neural network to extract minutiae without any preprocessing, and performs matching using a method designed for touch-based samples.
2020	Genetic matcher [108]	*ii)* Methods designed for 2-D touchless samples	Uses genetic algorithms to match minutiae-based templates.
2011	Neural matcher [25]	*ii)* Methods designed for 2-D touchless samples	Uses artificial neural networks to compare pairs of minutiae.
2016	Neural matcher [23]	*iii)* Methods designed for 3-D touchless samples	Compensates for perspective deformations of 2-D images by computing the best matching score obtained by applying a set of 3-D rotations to a 3-D model of the probe sample.
2015	Neural matcher [60]	*iii)* Methods designed for 3-D touchless samples	Is a minutiae-based matcher that compares minutiae coordinates in 3-D space.

Methods designed for 3-D touchless samples attempt to achieve improved recognition accuracy compared to 2-D minutiae-based approaches. One approach consists of compensating for the perspective deformations of 2-D images by computing the best match score obtained by applying a set of 3-D rotations to a 3-D model of the probe sample [23]. To exploit the additional information provided by 3-D fingerprint models, some biometric systems use matching algorithms that compare the minutiae coordinates in 3-D space [60]. In this case, a pair of minutiae is considered to correspond if the Euclidean distance between their 3-D coordinates in the spatially aligned samples is less than a certain threshold and if the differences between their angles in 3-D space are less than certain fixed values.

3.3.2 Approaches Based on Non-Minutiae Features

In the literature, there are some biometric recognition approaches designed for touchless fingerprint recognition systems that use features different from minutiae points to achieve accurate results in heterogeneous application scenarios. Specifically, these biometric recognition approaches can be divided into the following classes: *i)* methods based on algorithmic matchers, *ii)* methods based on computational intelligence

Table 5 Summary of approaches based on non-minutiae features for fingerprint recognition

Year	Method	Class	Approach
2011	Level zero features [61]	*i)* Methods based on algorithmic matchers	Uses level zero features (such as local texture patterns) and performs matching by using the Hamming distance operator.
2015	SURF [112]	*i)* Methods based on algorithmic matchers	Uses Speeded-Up Robust Features (SURF) to compute a template and performs matching by evaluating corresponding pairs of points.
2007	Local Gabor filters [45]	*ii)* Methods based on computational intelligence techniques	Uses a set of Gabor filters to compute biometric templates and performs matching by using an SVM classifier.
2016	LBP and LGC [117]	*ii)* Methods based on computational intelligence techniques	Uses the LBP and local gradient code (LGC) descriptors to compute a template and performs matching by using a nearest neighbor classifier.
2015	Scattering networks A [99]	*ii)* Methods based on computational intelligence techniques	Uses scattering networks to compute a template and performs matching by using a random forest classifier.
2017	Scattering networks B [79]	*ii)* Methods based on computational intelligence techniques	Uses scattering networks to compute a template and performs matching by using trained machine learning classifiers.
2018	Deep feature vector [13]	*iii)* Methods based on DL strategies	Uses a competitive coding algorithm in conjunction with a residual network and performs matching by using the Hamming distance operator.
2018	Partial fingerprints [68]	*iii)* Methods based on DL strategies	Performs the matching of partial fingerprints with 3-D fingerprint acquisitions by using multiple Siamese CNNs.
2019	Cross-domain [71]	*iii)* Methods based on DL strategies	Performs cross-domain matching between touchless and touch-based samples by using multiple Siamese CNNs.
2018	Pore extraction [18]	*iii)* Methods based on DL strategies	Uses multiple CNNs to estimate and refine pore coordinates.

techniques, and *iii)* methods based on DL strategies. Table 5 presents an overview of such methods.

Methods based on algorithmic matchers exhibit relevant differences depending on the application scenario for which they have been designed. Some methods are designed to perform biometric recognition based on low-resolution touchless fingerprint images using level zero features, such as local texture patterns, which are matched by using the Hamming distance operator [61]. Another method consists of computing Speeded-Up Robust Features (SURF) and evaluating the number of corresponding pairs of points [112].

Methods based on computational intelligence learn distinctive characteristics of samples with the aim of overcoming the nonidealities that can detrimentally affect touchless samples, such as perspective distortions, reflections, and low visibility of the ridge patterns. Some of these methods are based on feature extractors applied for heterogeneous machine learning applications, such as sets of local Gabor filters [45], or a combination of the LBP and local gradient code (LGC) descriptors [117]. Other methods are based on more descriptive feature extractors such as scattering networks [79, 99], which are filter banks of wavelets able to compute distinctive representations that are stable with respect to local affine transformations.

Methods that rely on DL strategies use feature extraction functions learned and optimized for touchless fingerprint samples. Some methods use feature extractors learned by deep neural networks to compare touchless samples, such as the recognition method presented in [13], which uses a competitive coding algorithm in conjunction with a residual network to extract templates that are compared using the Hamming function. There are also studies on matching partial fingerprints with 3-D fingerprint acquisitions by using multiple Siamese CNNs [68]. Multiple Siamese CNNs are also used to perform cross-domain matching between touchless and touch-based samples [71]. Deep neural networks can also be used to analyze ultrathin details of the fingertip (pores, incipient ridges, and local ridge characteristics). For example, the method described in [18] estimates and refines pore coordinates by using multiple CNNs.

4 Conclusions

Palmprints and fingerprints are the most commonly used hand characteristics for biometric recognition. Recent studies have introduced accurate touchless technologies that offer enhanced usability, acceptability, hygiene, and robustness to grease and dirt compared with traditional touch-based technologies.

This chapter has presented a literature review on touchless palmprint and fingerprint recognition systems, focusing on the technological perspective. In particular, it has analyzed every phase of the biometric recognition chain, considering acquisition systems, preprocessing techniques, and feature extraction and matching methods. This review has focused on both two- and three-dimensional technologies, highlighting recent advances enabled by computational intelligence approaches and deep neural networks.

From the presented analysis of the state of the art, it is evident that deep neural networks enable marked improvement in the robustness and accuracy of touchless palmprint and fingerprint recognition systems. However, there are still open problems to be solved in order to develop highly usable and accurate systems that are fully compatible with touch-based biometric databases.

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