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A Review of Fingerprint Feature Representations and Their Applications for Latent Fingerprint Identification: Trends and Evaluation

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ABSTRACT Latent fingerprint identification is attracting increasing interest because of its important role in law enforcement. Although the use of various fingerprint features might be required for successful latent fingerprint identification, methods based on minutiae are often readily applicable and commonly outperform other methods. However, as many fingerprint feature representations exist, we sought to determine if the selection of feature representation has an impact on the performance of automated fingerprint identification systems. In this paper, we review the most prominent fingerprint feature representations reported in the literature, identify trends in fingerprint feature representation, and observe that representations designed for verification are commonly used in latent fingerprint identification. We aim to evaluate the performance of the most popular fingerprint feature representations over a common latent fingerprint database. Therefore, we introduce and apply a protocol that evaluates minutia descriptors for latent fingerprint identification in terms of the identification rate plotted in the cumulative match characteristic (CMC) curve. From our experiments, we found that all the evaluated minutia descriptors obtained identification rates lower than 10% for Rank−1 and 24% for Rank−100 comparing the minutiae in the database NIST SD27, illustrating the need of new minutia descriptors for latent fingerprint identification.

INDEX TERMS Latent fingerprint identification, minutia descriptor, fingerprint feature representation, minutia descriptor evaluation.

I. INTRODUCTION

Latent fingerprint identification is an open problem that is attracting increasing interest due to its relevance to law enforcement [1]–[4]. A latent fingerprint could reveal the presence of a person at a crime scene. Further, a latent fingerprint may serve as a clue to lead police to a successful criminal apprehension; *e.g.*, the discovery of a criminal child pornography network in the USA, back in 2017, started from a fingerprint acquired from a digital photograph [5]. Furthermore, the misidentification of latent fingerprints could also lead to the release of a criminal or, even worse, to the apprehension of an innocent person [6], [7]. For example, as reported by The Innocence Project [7], a fingerprint of Brandon Mayfield was erroneously matched to a latent fingerprint found during the investigations of the train bombing in Madrid [8]; something similar happened to the Scottish detective Shirley McKie but at a different crime scene [6].

Existing automatic fingerprint identification systems (AFISs) are far from satisfying the requirements of justice departments, at least in terms of identification rate [9]. Table 1 summarizes state-of-the-art performance results for latent fingerprint identification. Note that the Rank−1 identification rate is lower than 78.4% in the context of

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TABLE 1. Rank−1 identification rate output by state-of-the-art latent fingerprint identification algorithms. These figures were obtained after comparing 258 latent fingerprints, taken from NIST SD27, against several background databases.

Algorithm	Year	Rank−1 identification rate (%)	Background Database size	Databases
Jain and Feng [11]	2011	74	29, 258	SD4, SD14, SD27
Medina-Pérez et al. with MCC [12]	2016	68.6	29, 258	SD4, SD14, SD27
Cao and Jain [3]	2018	78.3	10, 000	SD14, SD27
Cao and Jain [2]	2019	64.7	100, 000	SD14, SD27, and additional fingerprints from a forensic agency

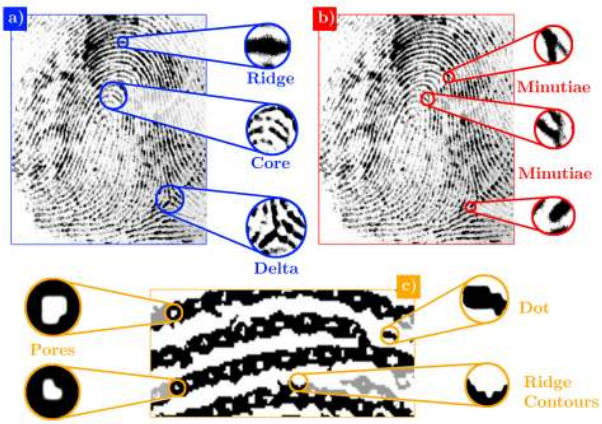

FIGURE 1. Fingerprint features. a) Level 1: Core, delta, and ridges. b) Level 2: Minutiae. c) Level 3: Pores, dots, and ridge contours.

the NIST SD27 database [10]. Therefore, latent fingerprints are an active research area with room for improvement in the next years.

Comparing fingerprints is possible through some features described by the ridges. Maltoni *et al.* [13] categorized these fingerprint features into three levels. Level 1 features, such as ridges, cores, and deltas (see Fig. 1-a), are highly visible in fingerprints. Level 2 features relate to minutiae. A *minutia* is a minute detail on the ridges of a fingerprint [14], often ridge ending or bifurcation (see Fig. 1-b). Level 3 features are intraridge details observable at the very fine level, such as ridge contours, sweat pores, and dots (see Fig. 1-c).

Additionally, although fingerprint acquisition methods have been classified according to different criteria [15], fingerprint acquisition for law enforcement application is usually performed using traditional offline methods [13]. Some experts have classified fingerprints acquired by these methods into the following categories: rolled impressions, plain (or flat) impressions, and latent fingerprints [13], [16], [17]. Whereas *impressions* are acquired under controlled conditions, *latent fingerprints* are unintentionally left by someone when manipulating objects and are thus particularly useful at crime scenes [18].

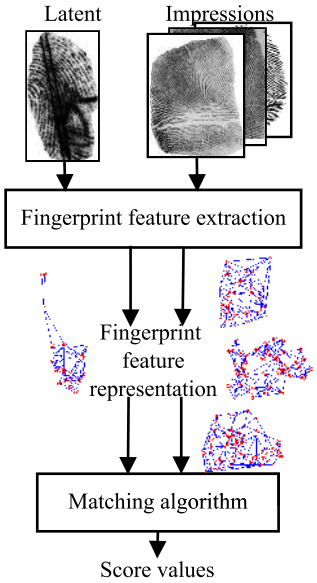

FIGURE 2. Diagram of a latent fingerprint identification pipeline.

Impressions and latent fingerprints are the inputs for two existing applications of fingerprint matching in biometrics: *fingerprint verification* and *latent fingerprint identification*. Fingerprint verification aims to verify the identity of an individual. Given the impression and claimed identity, the algorithm for fingerprint verification matches this impression with a previously stored impression from the claimed identity, and it returns whether the comparison is matching or non-matching [13], [19]. However, latent fingerprint identification searches a background database for the most similar impressions to the latent fingerprint in question [13], [19].

Matching algorithms (for either verification or identification) take two fingerprints to determine whether they have been obtained from the same finger. Fingerprints are captured via a fingerprint representation [2], [20]–[28] made of fingerprint features. Depending on the fingerprint feature representation, there are three types of matching algorithms: global, local, or hybrid [13]. A matching algorithm is said to be global if it works with a feature representation that captures the whole fingerprint, such as cores, deltas, or the global position of minutiae, and local if it works with a feature representation that captures a partial zone of a fingerprint. Hybrid-matching algorithms are two-step algorithms: they apply both local and global matching in that order [13].

In a latent fingerprint identification pipeline, the fingerprint feature representation constitutes a connecting data representation between the fingerprint feature extraction stage and the matching stage (see Fig. 2). The algorithms for feature extraction [1], [29]–[32] generate a representation of the fingerprint features from raw digital images; however, in this work, we have employed fingerprint features manually extracted by human experts. Next, the matching algorithms compare the latent fingerprint against multiple impressions using the same feature representation for the impression and the latent fingerprint to return sorted score values.

To improve the performance of a matching algorithm, the associated fingerprint representation must developed so that "fingerprint images belonging to the same finger form a compact cluster (low intraclass variations) and those belonging to different fingers occupy different portions of the space (high interclass variations)" [13].

Although using feature representations proposed for verification in latent fingerprint identification is commonly found in the literature [11], [12], [16], [33], [34], there is neither a study that aims to assess what feature representations are more suitable for latent fingerprint identification nor a study that explains whether the performance of an AFIS, with a hybrid-matching approach, is attributable to the global-matching algorithm or to the associated fingerprint feature representation and the corresponding local-matching algorithm. In contrast to [15], [35], our study aims to fill these gaps, and we focus on evaluating the relative merit of a feature representation, without considering feature extraction. Further, even though they may not be enough for the general case of latent fingerprint identification, we focus on evaluating minutia descriptors, as they are often applicable and thus quite popular. Each fingerprint in our database is expressed in terms of basic features (minutiae and ridge flow maps) that have been extracted by an expert, and so we take them as our ground truth. Using these basic features, we have reproduced some minutia descriptors reported in the literature. Our goal is to analyze how each of these minutia descriptors compares to one another for latent fingerprint identification in terms of local matching performance but independent of the global-matching algorithm. To do so, we introduce an evaluation protocol for quantifying the identification rate of minutia descriptors for latent fingerprint identification. In particular, we discuss the performance of nine minutia descriptors using the fingerprints in the database NIST SD27 [10]. Since all the minutiae of latent fingerprints in the NIST SD27 [10] are manually matched against a minutia of an impression, this is a closed-set identification application. Therefore, the performance indicators we use in our comparison are the identification rates plotted in the cumulative match characteristic (CMC) curve and the weighted Rank−20 identification rate computed from the CMC curve, according to the norm ISO/IEC 19795-1.

The main contributions of this paper are summarized as follows:

- An analysis of 50 fingerprint feature representations and their suitability for representing latent fingerprints.
- A new protocol to evaluate the relative merit of minutia descriptors for latent fingerprint identification.
- An experimental comparison of nine minutia descriptors, which are suitable for latent fingerprint identification according to our analysis.

The remainder of this paper is organized as follows. In section II, we review the most prominent fingerprint feature representations and analyze their feasibility for latent fingerprint identification. Section III introduces our protocol for evaluating the identification rate of minutia descriptors for latent fingerprint identification. In section IV, we discuss the experimental results of the evaluation of nine minutia descriptors using the NIST SD27 database [10]. Finally, in section V, we present our conclusions and future work.

II. REVIEW OF FINGERPRINT FEATURE REPRESENTATIONS

Fingerprint matching has been used for years [14]. However, fingerprint matching with electronic devices and algorithms has received wider attention with the expansion of its use in banking and commerce operations [36]–[40]. Early works, like those of Grasselli [21], Sirovich [41], Liu and Shelton [42], and Isenor and Zaky [39], presented noteworthy ideas for fingerprint feature representations and provided a coordinate system regarding the core and delta of the fingerprint [42] and early fingerprint feature representations based on the ridge flow, such as sampling matrix [21], slopes matrix [41], and graph representation [39]. Later, other works [22], [40], [43] started representing fingerprint features based on minutiae and their relationships with other fingerprint features. Many researchers [44]–[46] proposed minutia neighborhood representations that incorporate additional information related to fingerprint features.

Although minutia descriptors are the most popular feature representations for latent fingerprints (see Table 2 and Table 3), we briefly discuss some of the advantages and disadvantages of other representations to ensure this paper is self-contained. Therefore, we present in this section a review of 50 fingerprint feature representations and discuss their suitability for representing latent fingerprints. We start by providing a general overview of fingerprint feature representations (section II-A). Then, in sections II-B and II-C, the core of this review, we discuss minutia-based descriptors by dividing our discussion into two parts: minutia descriptors proposed for verification and minutia descriptors used for identification. With this division, we aim to show a trend toward representing latent fingerprints with minutia descriptors that have been previously proposed for fingerprint verification and the existence of minutia descriptors suitable for representing latent fingerprints but yet unused for latent fingerprint identification. Further, in this review, we consider four categories of minutia descriptors: image-based, minutiae-based, texture-based, and combined minutia. This last division is a modification of the taxonomy proposed by Feng and Zhou [47], including an additional category with minutia descriptors with some other combinations.

A. FINGERPRINT FEATURE REPRESENTATIONS, A GENERAL OVERVIEW

Fingerprint feature representations have been classified based on different criteria by some authors [13], [26], [35], [47], [48]. According to Vij and Namboodiri [48], fingerprint feature representations are global, local, combined, or transformation-based. A *global* representation describes the whole fingerprint, for example, the distance and

TABLE 2. Summary of 50 fingerprint feature representations classified according to 5 taxonomies. Column 4 classifies feature representations according to the fingerprint matching context: (V) verification and (I) identification. Column 5 classifies feature representations according to the level of the fingerprint feature employed: (1), (2), and (3). Column 6 classifies feature representations according to the type of feature representation: (G) global, (L) local, (GL) combinations of global and local, and (T) transform based. The last two columns are taxonomies exclusively for minutia descriptors. Column 7 classifies minutia descriptors according to the origin of the features: (Mtia) minutiae, (Tex) texture, and (Img) image. Column 8 classifies minutia descriptors according to the topology: (NN) nearest-neighbor and (FR) fixed-radius. PART I.

#	Fingerprint feature representation	Used in	Matching context	Fingerprint feature level [13]	Type of the feature representation [48]	Origin of the features [47]	Topology [13]
1	Shape and minutiae features	[40]	I	1, 2	G	–	–
2	Global orientation field descriptor	[56]	V	1, 2	G	–	–
3	Density map	[58]	V	1	G	–	–
4	Ridge coordinate system. RCS	[59]	V	1, 2	G	–	–
5	Ridge representation	[57] [11]	V I	1,2	G	–	–
6	Fingerprint shell	[61]	V	1,2	G	–	–
7	Ridge descriptor using Bezier curve	[62]	I	1, 2	G	–	–
8	Polyline	[60]	V	1	G	–	–
9	OrientationCode	[60]	V	2	T	Img	FR
10	3D features vector using wavelet decomposition	[52]	V	1	T	–	–
11	Fingercode	[64] [16]	V I	1	T	Img	FR
12	Minutiae and texture based representation	[65]	V	1 ,2	T	Mtia, Tex, Img	FR
13	DCT coefficients of a fingerprint	[54]	V	1	T	–	–
14	Location-Based Spectral Minutiae Representation. SML.	[55]	V	2	T	Mtia, Img	FR
15	Orientation-Based Spectral Minutiae Representation. SMO	[55]	V	2	T	Mtia, Img	FR
16	m-triplets with quaternion disc-harmonic moment	[27]	V	2	T	Mtia, Img	NN
17	Minutia descriptor using ConvNets	[2]	I	1, 2	T	Mtia, Tex, Img	FR
18	SymbolicString with bounding box	[45], [95], [96]	V	1, 2	GL	Mtia, Tex	NN
19	Ridge curvature map and minutia descriptor. RCM	[63]	V	1, 2	GL	Mtia, Tex, Img	NN
20	4-nearest-neighbor minutia	[69]	V	1, 2	L	Mtia	NN
21	Minutia windows	[43]	V	2	L	Mtia, Tex	NN
22	Binary segments	[44]	V	1, 2, 3	L	Mtia, Tex	FR
23	Pores descriptor	[89]	V	3	L	Img	FR
24	Structural Data Model	[22], [46]	V	2, 3	L	Mtia	FR
25	l-nearest minutiae	[23], [74], [97]	V	2	L	Mtia	NN
26	Minutiae list	[67]	V	1, 2	L	Mtia, Tex	NN
27	Minutia adjacency graph. Star	[50]	V	2	L	Mtia, Tex	FR
28	Ridge frequency around minutiae	[77]	V	1, 2	L	Tex	FR

TABLE 3. Summary of 50 fingerprint feature representations classified according to 5 taxonomies. Column 4 classifies feature representations according to the fingerprint matching context: (V) verification and (I) identification. Column 5 classifies feature representations according to the level of the fingerprint feature employed: (1), (2), and (3). Column 6 classifies feature representations according to the type of feature representation: (G) global, (L) local, (GL) combinations of global and local, and (T) transform based. The last two columns are taxonomies exclusively for minutia descriptors. Column 7 classifies minutia descriptors according to the origin of the features: (Mtia) minutiae, (Tex) texture, and (Img) image. Column 8 classifies minutia descriptors according to the topology: (NN) nearest-neighbor and (FR) fixed-radius. PART II.

#	Fingerprint feature representation	Used in	Matching context	Fingerprint feature level [13]	Type of the feature representation [48]	Origin of the features [47]	Topology [13]
29	Orientation based descriptor	[49], [82] [24], [79]	V I	1, 2	L	Mtia, Tex	FR
30	Delaunay triangulation	[72]	V	2	L	Mtia	NN
31	Localized secondary features	[74]	V	2	L	Mtia	NN
32	Delaunay triangulation	[73]	V	1, 2	L	Mtia, Tex	NN
33	Adjacent Features Vector. AFV	[78]	V	1, 2	L	Mtia, Tex	FR
34	K-Plet	[70]	V	2	L	Mtia	NN
35	Minutiae triangle	[98]	V	1, 2	L	Mtia, Tex	NN
36	Minutiae-based descriptor	[24] [79]	V I	2	L	Mtia	FR
37	Texture-based descriptor	[24]	V	1, 2		Mtia, Tex	
38	Minutiae and orientation based descriptor	[79], [99], [12]	I	1, 2	L	Mtia, Tex	FR
39	Local Relative Location Error Descriptor. LRLED	[100]	V	2	L	Mtia	FR
40	Local skeleton descriptor	[75]	V, I	1, 2	L	Mtia, Tex	FR
41	Minutia and sample points neighboring	[101]	V	1, 2	L	Mtia, Tex	FR
42	Spiral-partitioning scheme	[81]	V	1, 2	L	Mtia, Tex	FR
43	Minutia Cylinder Code.	[25], [97] [102] [34], [33], [92], [12]	V Indexing I	2	L	Mtia	FR
44	Vicinities of minutiae binary features vector	[85]	V	2	L	Mtia	FR
45	Triplet-based descriptor	[93]	I	2	L	Mtia	NN
46	m-triplets. MTP	[51] [27] [12]	V I	2	L	Mtia	NN
47	Random local region descriptor. RLRD	[82]	V	1, 2	L	Mtia, Tex	FR
48	Local minutiae-ridge-orientation descriptor	[84]	V	1, 2	L	Mtia, Tex	NN, FR
49	Minutiae vicinity descriptor	[76]	I	2	L	Mtia	NN
50	The arrangement structure	[48]	V	2	L	Mtia	NN

the angle between the core and the delta of a fingerprint or the positions of minutiae in a fingerprint.

A *local* representation describes small areas of a fingerprint, generally around a minutia (level 2 feature). Local representations are often known as minutia descriptors [47], [49]. A *minutia descriptor* is a combination of the minutia representation, which includes its coordinate and angle from the origin of the image (ISO/IEC 19794-2:2005), with additional information about other neighboring features [22], [23], [50]. For example, the orientation-based minutia descriptor [49] incorporates information about the ridge orientation in a neighborhood around a minutia, while the m-triplet [26], [51] incorporates information about the distance and the angles between three neighboring minutiae.

A *combined* representation describes the whole fingerprint by using both global and local feature representations, e.g., combining minutia descriptors and the distance of minutiae from the core. A *transform-based* representation could be either global or local but uses some transforms, such as digital wavelet transform [52], [53], digital cosine transform [54], Fourier-Mellin transform [55], or short-time Fourier transform [2].

Although global [40], [56]–[62] or combined [45], [48], [63] feature representations contribute to a highly accurate identification, a drawback of using either of these representations is that they are not always applicable because the required features are not always present in latent fingerprints. For example, a coarse visual review of the NIST SD27 database [10] shows that at least 65 latent fingerprints –representing 25% of the database– do not present clearly visible cores. Moreover, latent fingerprints present scars and background noise that interrupt ridge flow (see Fig. 3). Therefore, due to the requirement of the presence of global features, these fingerprint feature representations are not always suitable for representing latent fingerprints.

Some authors [2], [27], [52], [54], [55], [60], [64], [65] have proposed fingerprint feature representations based on transforms. Nevertheless, transform-based feature representations are sensitive to brightness and rotation variations in the fingerprint [48]. Therefore, transform-based representations are not always suitable for latent fingerprint identification because the orientation of some latent fingerprints is difficult to determine [28], [30] and their brightness varies often. Indeed, Sankaran et al. [16] experimentally showed a Rank−10 identification rate of (35.4%) using Fingercode [64] for latent-to-latent fingerprint matching on the IIIT-D latent database [66], the lowest among seven matching algorithms.

B. MINUTIA DESCRIPTORS USED SOLELY IN VERIFICATION

Unlike global representations, minutia descriptors employ fingerprint features that are present on many latent fingerprints with identification value. Moreover, minutia descriptors are less sensitive than global, combined, and transform-based feature representations to nonlinear distortions, brightness variations, and lack of features of latent fingerprints [67]. Therefore, minutia descriptors have become the most widely used fingerprint feature representations for latent fingerprints.

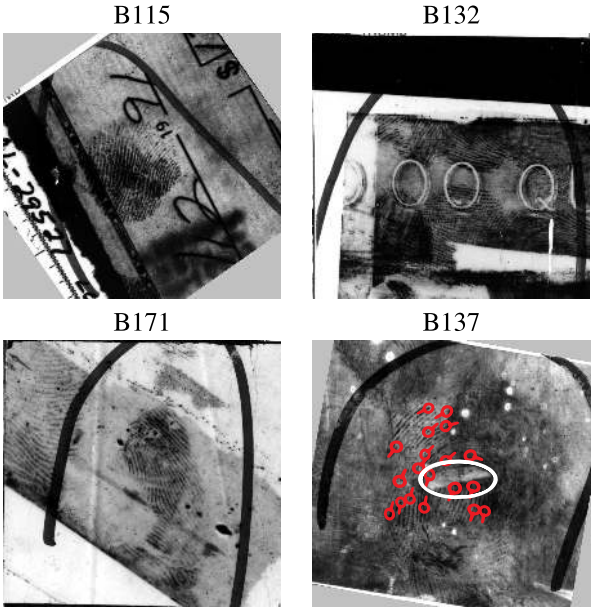

FIGURE 3. Examples of latent fingerprints without a visible core. B115 is the code for the latent fingerprint number 115 of bad quality in the NIST SD27. B137 is a latent fingerprint with the ridge flow interrupted (we surrounded the interruption with a white ellipse).

1) IMAGE-BASED MINUTIA DESCRIPTORS

An image-based minutia descriptor is a fingerprint feature representation of the raw image, binarized image, or enhanced image around a minutia in a circular or square region [47] (see Fig. 4-a,b,c). Some authors [2], [35], [67], [68] have proposed square areas of 8×8, 16×16, and 24×24 pixels for computational efficiency. Consequently, image-based minutia descriptors are also fixed-radius minutia descriptors [13].

An inconvenience of image-based minutia descriptors is that they require more computational time than other minutia descriptors to be compared regarding the window size [35]. Additionally, the image information around a minutia could be represented using transforms [2], [27], [55], becoming a transform-based feature representation and suffering similar issues as the transform-based feature representations. Another disadvantage of image-based minutia descriptors is related to noisy areas in latent fingerprints, which can largely differ from their mated area in the impressions because latent fingerprints present noisy backgrounds, brightness variations, image quality variations, and scars (see Fig. 3). These characteristics make image-based minutia descriptors less suitable for representing latent fingerprints than other minutia descriptors.

2) MINUTIA-BASED MINUTIA DESCRIPTORS

A minutia-based minutia descriptor represents the relationship between minutiae in a neighborhood, such as distance and direction difference. Some authors have defined this

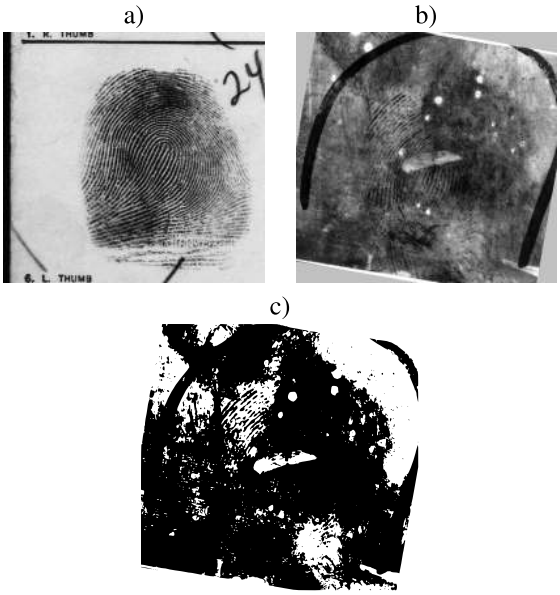

FIGURE 4. Mated fingerprint pair (impression and latent fingerprints) number 137 of bad quality (B137) in the NIST SD27 database showing the low quality and noise of a latent fingerprint. a) Impression, b) raw grayscale image of the latent fingerprint, and c) binarized image of the latent fingerprint.

neighborhood using nearest-neighbor minutiae, while others have defined this neighborhood as all the minutiae in a fixed-radius area [47].

A disadvantage of nearest-neighbor minutia descriptors relates to the presence of absent or spurious minutiae, which is common on latent fingerprints. For example, Zhang and Wang [69] introduced the 4-nearest-neighbor minutiae, describing the neighborhood of a minutia with the four nearest minutiae. The authors code each neighboring minutia as a vector with its distance from the main minutia, orientation difference, angle between its orientation and the connecting edge, and the angle between its connecting edge and the connecting edge of the main minutia with the next minutia in the clockwise direction. Similarly, Chikkerur et al. [70] proposed K-Plet for representing fingerprint features using minutiae. K-Plet consists of a neighborhood of K minutiae around a main minutia. Each minutia of the neighborhood is defined according to its local radial coordinates, including distance, orientation difference, and angle with respect to the main minutia of the neighborhood. Neighboring minutiae are selected by quadrants to achieve a representation of each quadrant. However, this selection makes K-Plet unsuitable for representing latent fingerprints, which suffer from the existence of spurious or absent minutiae and lack of minutiae in some quadrants, mostly in noisy zones.

Another nearest-neighbor minutia descriptor widely used for minutiae is the minutiae triplet. A special case of minutiae triplets is the Delaunay triangulation [71] used by some authors for fingerprint matching [72], [73]. The limitation of the Delaunay triangulation for representing latent fingerprints relates to the high number of absent and spurious minutiae: different Delaunay triangulations may be obtained from mated fingerprints when they present different sets of minutiae, resulting in misidentification.

Jea and Govindaraju [74] presented a modification to the minutia descriptor of Jiang and Yau [23] by considering the two nearest minutiae to each main minutia according to the angular distances rather than the Euclidean distance proposed by Jiang and Yau [23]. They also removed the minutia type and ridge count, thus making this minutia descriptor suitable for representing partial and noisy fingerprints according to their analysis. They reported an improvement in the minutia descriptor of Jiang and Yau [23] based on their experimental results on fingerprint verification. Hence, we compare both minutia descriptors on latent fingerprint identification but without employing a global-matching algorithm.

Fixed-radius minutia descriptors are less affected by absent and spurious minutiae. However, minutiae near the border area could be in or out of the neighborhood due to nonlinear distortions. For instance, the structural data model proposed by Hrechak and McHugh [22] creates a minutia descriptor as a nine-dimensional vector including the number of minutiae of each type in a neighborhood of fixed radius. Thus, for a low radius, the number of minutiae decreases the identification value of the descriptor, and for a large radius, nonlinear distortion means that minutiae in the border area could be in or out of the descriptor. Additionally, the authors defined eight types of minutiae: termination, bifurcation, island, spur, crossover, bridge, and small crests. Nevertheless, some authors [25], [74]–[76] have claimed that the use of several minutia types is not suitable for representing latent fingerprints because they can easily be confused due to the difference of pressure of the finger over the surface and the background noise of the surface.

Wahab et al. [46] modified the structural data model to improve the local-matching algorithm. However, their proposal presented similar deficiencies for latent fingerprint identification.

3) TEXTURE-BASED MINUTIA DESCRIPTORS

A texture-based descriptor employs the texture information around a minutia to represent fingerprints. Texture information may include ridge orientation, frequency, or period. Several authors [56], [77], [78] have employed the texture information around minutiae to represent fingerprints. They have created minutia coordinate systems based on ridges or have included additional components to the (ISO/IEC 19794-2:2005) minutiae representation.

For example, Lee et al. [77] included the ridge frequency as a new component of the minutia representation. They defined the ridge frequency as the number of ridges within a predefined window around minutia. The ridge frequency was used later in latent fingerprint representation by other authors [11], [79] and improved the identification rate.

Other studies [56], [78], [80]–[82] proposed minutia descriptors similar to the orientation-based minutia descriptor proposed by Tico and Kuosmanen [49] (discussed in

subsection II-C3). However, these studies made the orientation-based minutia descriptor rely on the global features of the fingerprint, creating descriptors that are more affected by nonlinear distortion, which is often present on latent fingerprints.

As an exception, the work of Shi and Govindaraju [81] does not employ global features but rather modifies the criteria to select the sampled points using a spiral partition scheme for fingerprint verification. In addition, they combined the texture information with minutiae in a neighborhood. According to their experimental results on fingerprint verification, we propose that it is worth exploring this variation to improve the performance of orientation-based minutia descriptors for latent fingerprint representation.

4) COMBINED MINUTIA DESCRIPTORS

The combination of various fingerprint features in minutia descriptors is beneficial for representing latent fingerprints with a small area but with an identification value [83]. Indeed, several studies [11], [24], [57], [60], [63], [79], [81], [84] have combined minutia descriptors based on different fingerprint features and obtained encouraging results. For example, Feng [24] proposed a minutia descriptor combining a frequency-based descriptor and a minutiae-based descriptor. This combined minutia descriptor was subsequently adapted to represent latent fingerprints by Jain et al. [79] and Jain and Feng [11] and improved the identification rate that had been reported thus far.

In contrast, some proposed combinations are not suitable for latent fingerprint identification. For example, the performance of the location-based spectral minutiae representation and the orientation-based spectral minutiae representation [55] decreases when the number of absent or spurious minutiae is greater than 20%. Similarly, the keypoint [84] is a combination of minutiae-based, texture-based, and orientation-based descriptors. However, a valid keypoint should contain at least n neighboring minutiae within a circle of radius R. Both minutia descriptors are sensitive to the lack of minutiae often suffered by latent fingerprints.

Some minutiae-based descriptors introduced the ridge count between minutiae in a neighborhood [23], [43], [50], [85], creating combined-feature minutia descriptors. For instance, Chen and Kuo [43] proposed a minutiae-based descriptor that includes the ridge count between minutiae in a specified neighborhood with respect to the main minutia (the minutia selected as the coordinate origin of the minutia descriptor). Furthermore, Jiang and Yau [23] described a minutia descriptor by minutia type, distance, ridge count, direction, and radial angle from the main minutia to each of the l-nearest minutiae in a neighborhood. In contrast, some authors [74], [86] have claimed that ridge count and minutia type are not feasible for some latent fingerprints because minutia type can be easily confused and ridge count is affected by scars or noisy zones that are often present in latent fingerprints (see Fig. 3). Thus, to use ridge count in latent fingerprints, it would be necessary to determine the quality of the ridges. However, because Cao and Jain [2] proposed exploring the use of ridge count for latent fingerprint identification, we determined its effect by comparing the identification rates of a pair of minutia descriptors with [23] and without [74] ridge count.

C. MINUTIA DESCRIPTORS USED FOR IDENTIFICATION

1) IMAGE-BASED MINUTIA DESCRIPTORS

Most image-based minutia descriptors [55], [60], [63], [65], [87]–[89] have been employed only for fingerprint verification due to their limited applicability for latent fingerprint identification. However, some authors [1], [2], [28], [32], [90], [91] have recently employed deep learning for latent fingerprint identification by primarily using raw images of latent fingerprints. For example, Cao and Jain [2], [3] trained 14 different convolutional neural networks with multiple patches extracted for the same minutia with different sizes and at different locations. All patches of a minutia corresponded to the same class. They employed different images of the same fingerprint impression to obtain different patches. Each convolutional neural network output a 128-dimensional vector as the feature vector of the minutia. Hence, a minutia descriptor is the concatenation of a subset of the 14 feature vectors output by the 14 convolutional neural networks.

Additionally, the authors generated a set of virtual minutiae, one by each nonoverlapping block, to overcome the lack of real minutiae in latent fingerprints. Consequently, they represented the whole latent fingerprint using minutia descriptors with the output of the convolutional neural networks for virtual and real minutiae. The matching score between two minutia descriptors is computed based on the cosine distance. One of the main contributions of this study is the Rank-1 identification rate achieved (64.7%) for comparing latent fingerprints in the NIST SD27 database against a background database with 100, 000 impressions, which involved fully automated the feature extraction, except in the region of interest.

2) MINUTIA-BASED MINUTIA DESCRIPTORS

Minutia-based minutia descriptors are the most widely used fingerprint feature representation for latent fingerprint identification [12], [26], [33], [34], [92]. One of the most popular descriptors is the Minutia Cylinder-Code (MCC), proposed by Cappelli et al. [25] (see Table 3). The main minutia of the MCC is rotated with a predefined step, and each rotation of the minutia incorporates a slice to a cell-discretized cylinder. Each slice presents a predefined number of cells. For each cell, a numerical value is calculated by accumulating the contributions of the minutiae belonging to the neighborhood. Several authors [12], [33], [34], [92] have successfully employed MCC for latent fingerprint identification. Since MCC encodes the spatial and directional relationships between the minutia and its neighbor in a fixed-radius area, it is a suitable fingerprint feature representation

for latent fingerprints. The expanded triangle set proposed by Hernández-Palancar et al. [76] uses Delaunay triangulation to represent latent fingerprints. Delaunay triangulation builds minutia descriptors by relating near points [71] (minutiae in a fingerprint), which is suitable for latent fingerprint representation. However, absent and spurious minutiae affect these fingerprint representations. Indeed, the authors reported a Rank−1 identification rate of 58.13% when comparing 258 latent fingerprints against a background database of 29, 258 impressions, and this Rank−1 identification rate was lower than that reported by Medina-Pérez et al. [12] (68.6%), who also used a minutia-based descriptor [51] based on the relation among three minutiae.

Hoyle et al. [93] mined minutia triangles to find distinctive features. They used a minutia-triplet descriptor, where any combination of three minutiae with a distance lower than a threshold formed a triplet. The authors used pairwise distances, ridge count, and whether each pairwise minutia lies on a shared-ridge segment. However, the authors did not report the performance of their algorithm on a latent fingerprint database. In addition, by removing the ridge count, the minutia-triplet descriptor is similar to another proposed by Medina-Pérez et al. [51]

Medina-Pérez et al. [51] introduced m-triplets. An m-triplet includes three minutiae arranged clockwise in a set and contains the maximum, middle, and minimum distances between minutiae, the angles required to rotate the direction of a minutia to superpose it to the vectors associated with the other two minutiae in the triplet, and the angle required to rotate the direction of a minutia to superpose it to the direction of the other two minutiae. Later, Medina-Pérez et al. [12] used the m-triplets [51] for latent fingerprint representation, achieving a Rank−1 identification rate of 68.6% when comparing the latent fingerprints in the NIST SD27 [10] against a background database of 29, 258 impressions from three different NIST databases. The latent fingerprint identification algorithm achieves similar identification rate using three minutia descriptors: m-triplets 68.6%, MCC 69% [25], and a neighboring minutia-based descriptor 64.3% [11], indicating that the global-matching algorithm performs well with these three minutia descriptors.

3) TEXTURE-BASED MINUTIA DESCRIPTORS

Bohné and Despiegel [75] presented the local skeleton descriptor, which is a coordinate system based on a selected curve segment along the direction of the ridge flow. Minutiae around a predefined neighborhood are projected on the local skeleton descriptor. The coordinate of the minutia is the algebraic curvilinear distance between the projection of the minutia on the curve segment and the signed ridge count between the minutia and the projection of the minutia on the curve segment. Although this fingerprint feature representation was used for latent fingerprints, the performance achieved was low; namely, the Rank−1 identification rate was below 35% when comparing latent fingerprints in the NIST SD27 database [10] against a background database with 1, 258 impressions.

The orientation-based minutia descriptor, published by Tico and Kuosmanen [49], characterized each minutia location according to the orientation of the ridges in sampled points around a minutia regardless of the position and orientation of the finger. This descriptor is a fixed-radius and texture-based minutia descriptor that describes ridge orientation in local representations around a minutia. These properties make it suitable for latent fingerprint feature representation.

The orientation-based minutia descriptor [49] has been improved by other authors [11], [24], [79] for fingerprint verification and latent fingerprint identification. Feng [24] proposed a texture-based minutia descriptor incorporating the ridge frequency to the ridge orientation at each sampled point in a fixed-radius neighborhood for fingerprint verification. Later, other authors [11], [79] employed this texture-based minutia descriptor with other descriptors for improving the identification rate of latent fingerprint identification.

4) COMBINED MINUTIA DESCRIPTORS

Jain and Feng [11] combined various minutia descriptors for latent fingerprint identification. Although the authors did not report a new minutia descriptor, they showed the convenience of combining many fingerprint features and minutia descriptors. They improved the Rank−1 identification rate to up to 74% when comparing latent fingerprints in the NIST SD27 database [10] against a background database of 29, 257 impressions from three different NIST databases.

Finally, other authors [44], [89], [94] have reported fingerprint feature representation with level 3 features. However, Jain and Feng [11] published a study showing that level 3 features do not improve the identification rates achieved with level 2 features on latent fingerprint identification, at least using the NIST SD27 database [10].

D. SUMMARY OF THE REVIEW OF FINGERPRINT FEATURE REPRESENTATIONS

Table 2 and Table 3 summarize our review of 50 fingerprint feature representations classified according to five taxonomies. We have included the classification of the fingerprint feature representations in terms of two more taxonomies proposed by Maltoni et al. [13] according to the topology of the representation and the level of the features employed. Table 2 and Table 3 show that 39 of the 50 fingerprint feature representations revised include local representations; furthermore, 30 are minutia descriptors, which supports our interest in minutia descriptors.

In Section II-B and Section II-C, we discussed the robustness of 30 minutia descriptors to nonlinear distortions, background noises, brightness variations, and the insufficient number of features on latent fingerprints. Moreover, we analyzed whether these descriptors were used for latent fingerprint identification. From these analyses, we ended up choosing nine minutia descriptors to conduct our

TABLE 4. Minutia descriptors selected to be evaluated with the proposed evaluation protocol. We have defined a minutia descriptor ID indicating the authors to be used in our experiments.

Minutia descriptor ID	Minutia descriptor	Reference
J&Y	l-nearest-neighbor descriptor	[23]
T&K	Orientation-based descriptor	[49]
J&G	A modification to the l-nearest-neighbor descriptor without ridge count and minutia type	[74]
Feng	Texture-based minutia descriptor	[24]
Jain et al.	Minutia-Neighborhood	[79]
S&G	A modification to the orientation-based descriptor	[81]
MCC	Minutia Cylinder Code	[25]
MTP	m-triplets	[51]
C&J	Minutia descriptor using ConvNets	[2]

experimental comparison (see Table 4). Among these nine minutia descriptors, we included two pairs of minutia descriptors (J&Y and J&G) and (T&K and Feng) with the aim of evaluating the impacts of ridge count, minutia type, and ridge frequency on latent fingerprint identification. The minutia descriptor proposed by J&Y [23] employs ridge count and minutiae type, but the minutia descriptor proposed by J&G [74] is a modification that does not use ridge count and minutiae type. Moreover, the descriptor proposed by Feng [24] incorporates ridge frequency in the orientation-based minutia descriptor T&K [49].

III. EVALUATION PROTOCOL FOR MINUTIA DESCRIPTORS IN LATENT FINGERPRINT

Having selected minutia descriptors in terms of suitability for latent fingerprint identification, we now proceed to elaborate on the evaluation protocol to be used for obtaining an overall conclusion. Our evaluation protocol aims to quantify the suitability of minutia descriptors for representing latent fingerprints by performing only local matching and using the same fingerprint database: NIST SD27 [10]. We use the local matching algorithm proposed with each minutia descriptor to compute the similarity between each minutia of the latent fingerprint and each minutia of the impressions [11].

Our evaluation protocol for minutia descriptors is partially inspired by the one proposed by Feng and Zhou [47]. Feng and Zhou [47] evaluated minutia descriptors for fingerprint verification. Therefore, their protocol compares minutia descriptors computed from mated impressions. They used fingerprint features automatically extracted from the database FVC2002 DB1_A [103]. Further, they employed (precision vs. recall) as the evaluation metric. In contrast, we compare all minutiae in latent fingerprints against all minutiae in impressions of the database to determine the performance of each minutia descriptor. Additionally, we evaluate the results of the local-matching algorithms against a ground truth manually marked by latent examiners and ridge flow maps manually marked by the authors. Furthermore, we employ CMC [104] curves as an evaluation measure adopting the norm ISO/IEC 19795-1, which indicates that CMC curves should be used for closed-set identification, while CMC and DET or ROC curves [105], [106] should be used for open-set identification.

As numerical measures of the CMC curve, we use the Rank−1, Rank−100, and weighted Rank−20 identification rates [107]. The Rank−1 and Rank−100 identification rates are well-known metrics of the CMC curve that quantify the ratio of correct identifications in the first place and among the 100 first ranks, respectively, returned by an identification algorithm. On the other hand, the weighted Rank−M identification rate proposed by DeCann and Ross [107] is the weighted sum of the identification rate of the first M ranks in the CMC curve, assigning higher weights to lower ranks. Those weights are computed as the inverse of the rank number $\left(w_i = \frac{1}{Rank_i}\right)$ and normalized such that $\sum w_i = 1$ [107].

The input for our evaluation protocol is a set of minutia descriptors extracted from latent fingerprints, a set of minutia descriptors extracted from impressions, an algorithm (δ) that locally matches the minutia descriptors of the latent fingerprints against the minutia descriptors of the impressions, and the set of matching minutiae as the manually marked latent examiners (see Algorithm 1).

First, we match every minutia descriptor of the latent fingerprints against every minutia descriptor of the impressions. Next, we compare the matching results of the local-matching algorithm with a ground truth, adding each matching pair to matching or nonmatching lists. Finally, from these lists, we compute the CMC curve to measure the identification rate of the minutia descriptor. Fig. 5 shows the flow diagram of the evaluation protocol. An implementation of this evaluation protocol for minutia descriptors of latent fingerprints using C# is available at: Evaluation protocol code.

IV. RESULTS AND DISCUSSION

Our experiments show the identification rates of nine minutia descriptors in terms of their CMC curves. We evaluated two possible scenarios for local matching according to the orientation difference between minutiae described by Kovács-Vajna [67]: minutia pairs with an orientation difference between $[-\pi/4, \pi/4]$ (restricted rotation) and minutia pairs without orientation restriction (free rotation).

The latent fingerprint database employed in our experiments is the NIST SD27 database [10], which is a public database with 258 latent fingerprints and their mated impressions with matching minutiae manually marked by latent examiners; the database comprises 5, 460 minutiae in the latent fingerprints and 27, 426 minutiae in the impressions. To explore both scenarios, we computed the orientation differences of the mated minutiae pairs on NIST SD27 [10] and found that 457 (8.37% of the database) mated minutiae pairs have an orientation difference $> \pm\pi/4$. Additionally, we used a proprietary database to train the minutia descriptor C&J [2] since we do not have access to the databases employed in their experiments.

Finally, in our experimental setup, to avoid differences related to hardware, we performed our experiments simulta-

Algorithm 1 Evaluation Protocol for Minutia Descriptors on Latent Fingerprints

function evaluationProtocol (L, T, δ, H)
Data:
- $L = \{L_1, L_2, \ldots, L_n\}$, where L_i is the set of minutia descriptors extracted from the i-th latent fingerprint.
- $T = \{T_1, T_2, \ldots, T_m\}$, where T_j is the set of minutia descriptors extracted from the j-th impression.
- $\delta(L_i, T_j)$ is an algorithm that locally matches the minutia descriptors of L_i and T_j. It returns a set M of matching triplets (q, p, s), where q and p are minutiae of the latent fingerprints and impressions (respectively) being compared; s is the similarity value of q and p computed from their respective minutia descriptors; and M is empty at first.
- H is the set of true matching minutia pairs (q, p) provided by latent examiners (ground truth), where q belongs to a latent fingerprint and p belongs to the true matching impression.

Result: CMC curve points
begin
  Let $M \longleftarrow \phi$ be the set of matching triplets
  Let $N \longleftarrow \phi$ be the set of nonmatching triplets
  foreach $L_i \in L$ **do**
    foreach $T_j \in T$ **do**
      Match locally the latent fingerprint with descriptors L_i against the impression with descriptors T_j and store the resulting matching triplets in R; i.e. $R \leftarrow \delta(L_i, T_j)$
    end
    foreach $(q, p, s) \in R$ **do**
      if $(q, p) \in H$ **then**
        $M \leftarrow M \cup \{(q, p, s)\}$
      else
        $N \leftarrow N \cup \{(q, p, s)\}$
      end
    end
  end
  Compute and return the CMC curve from M and N
end

neously on a server with an Intel Xeon E5-2670 v3 processor (48 virtual processors), 1 TB of RAM, and a 1 TB hard drive.

A. ANALYSIS OF THE IDENTIFICATION RATE OF THE MINUTIA DESCRIPTORS REGARDING THE CMC CURVE

The CMC curve reports comparisons between the minutiae of latent fingerprints (5, 460) against minutiae of impressions (27, 426) on NIST SD27 [10]. We plotted the x-axis of this curve on a logarithmic scale to emphasize the identification rate of the local-matching algorithms for the first 100 ranks. We chose a logarithmic scale because fingerprints usually present between 100 and 200 minutiae [13], and thus,

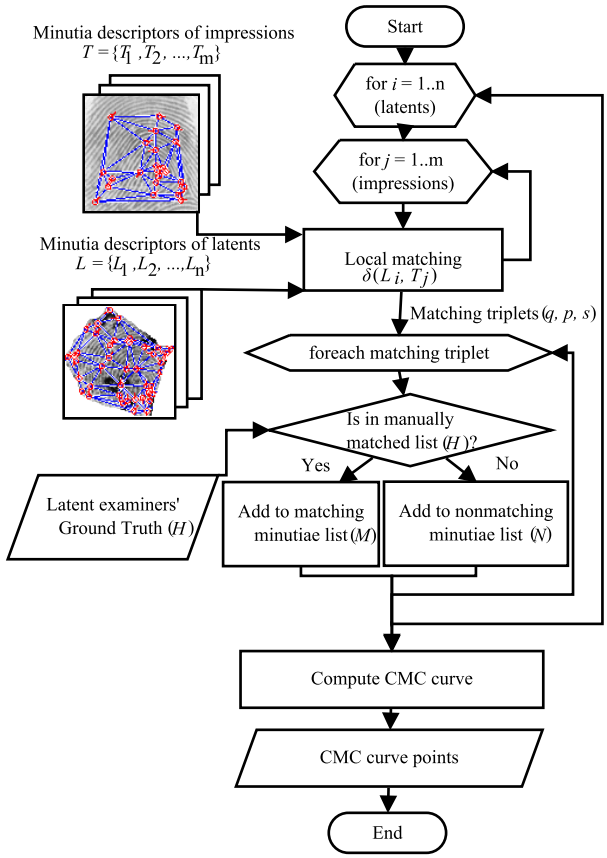

FIGURE 5. Flow diagram of the evaluation protocol for minutia descriptors on latent fingerprints.

matching algorithms rarely compare more than 100 minutiae. Notice that there are observable differences between minutia descriptors in terms of their CMC curves for the first 100 ranks, indicating that the selection of the minutia descriptor might impact the performance of an AFIS.

Since NIST SD27 has 8.37% of the matching minutiae pairs with an orientation difference $> \pm\pi/4$, local-matching algorithms with restricted fingerprint rotation falsely reject around 8% of the matching minutiae pairs, which explains the horizontal line of the curves starting at an identification rate of $\approx 82\%$ in Fig. 6-a.

Table 5 corroborates the visual results depicted in Fig. 6 by three values of identification rates.

MCC describes the best CMC curves until Rank−100 in both scenarios. MCC intrinsically combines all information of minutiae and ridges by neighborhood. Each cell of a slice in a cylinder captures the contribution of their nearest minutiae with similar orientation to the main minutia, which is how MCC combines the information of minutiae and ridges: ridges determine the orientation of a minutia, and MCC captures all minutiae in a neighborhood. Moreover, MCC has soft borders of the neighborhood to solve the problem of minutiae near the border, which may be in or out of the local structure depending on the nonlinear distortion of the fingerprint. Consequently, MCC achieved the highest identification rates for most of the rank values lower than 100 in both scenarios.

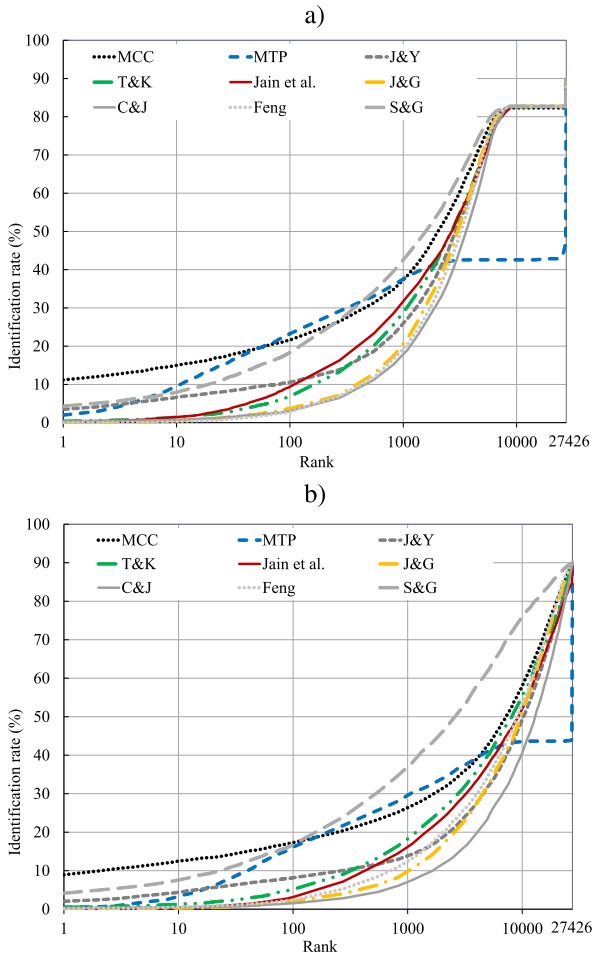

FIGURE 6. CMC curve Rank−27, 426 of the selected minutia descriptors comparing minutiae in the NIST SD27 database. The x-axis is plotted on a logarithmic scale to emphasize the identification rate of the local-matching algorithms for the first 100 ranks. We performed two minutia descriptor evaluations considering a) restricted fingerprint rotation and b) free fingerprint rotation.

Nevertheless, note that the identification rates do not indicate that the problem of local representation of latent fingerprints with minutia descriptors is solved. Indeed, MCC ranks the matching minutia descriptor of the 100 first ranks 21.56% of the time with restricted rotation. Therefore, further research is needed to decrease the percentage of time (approximately 80%) that the matching minutia descriptor is not identified among the 100 first ranks.

In addition, the curves and metrics depict that J&Y achieved a greater identification rate than J&G regarding all metrics in both scenarios. Consequently, we claim that employing ridge count and minutia type is suitable for latent fingerprint identification, at least for local matching and considering the 100 top-scored minutiae of the impressions in the NIST SD27 [10] database. Furthermore, Fig. 6 and Table 5 show that the minutia descriptor Feng achieved lower identification rates than T&K in both scenarios. Therefore, ridge frequency is not an extended feature that improves the latent fingerprint identification while considering the 100 top-scored minutiae of the impressions in NIST SD27 [10].

TABLE 5. Identification rate output by the evaluation protocol for the selected minutia descriptors. We list the identification rates for two scenarios considering a) restricted fingerprint rotation and b) free fingerprint rotation. Minutia descriptors are sorted in descending order according to the Rank−1 identification rate. We use bold typeface to emphasize the highest identification rate for each rank; the higher the identification rate is, the better performance of the minutia descriptor.

(a)

Minutia descriptor	Rank−1 Identification Rate	Rank−100 Identification Rate (%)	weighted Rank−20 (%)
MCC [25]	**9.23**	21.56	**12.34**
S&G [81]	2.84	18.24	5.54
J&Y [23]	2.36	10.51	4.55
MTP [51]	0.97	**23.21**	4.86
C&J [2]	0.24	3.00	0.51
T&K [49]	0.13	6.79	0.75
Jain et al. [11]	0.05	9.32	0.70
J&G [74]	0.04	3.61	0.26
Feng [24]	0.02	2.82	0.12

(b)

Minutia descriptor	Rank−1 Identification Rate	Rank−100 Identification Rate (%)	weighted Rank−20 (%)
MCC [25]	**7.51**	**17.25**	**10.15**
S&G [81]	2.67	16.72	5.28
J&Y [23]	1.47	8.15	2.91
T&K [49]	0.29	5.11	0.77
MTP [51]	0.24	16.08	1.58
C&J [2]	0.09	1.50	0.34
Feng [24]	0.09	2.29	0.3
J&G [74]	0.04	2.03	0.13
Jain et al. [11]	0.02	3.10	0.17

We also found that the variations between the identification rates with restricted and free rotation are lower than 2% for Rank−1, 4% for weighted Rank−20, and 8% for Rank−100. Considering that 8.37% of the matching minutiae pairs in NIST SD27 have an orientation difference $> \pm\pi/4$, we claim that fingerprint rotation does not affect the performance of minutia descriptors in terms of the identification rates Rank−1, Rank−100, and weighted Rank−20, at least in the NIST SD27 database.

Finally, we emphasize the results of the minutia descriptor C&J. Although this descriptor can be used for automatic fingerprint feature extraction and we trained it with a different database than the one employed by the authors, its identification rates are similar to most of the other minutia descriptors (see Table 5). Additionally, we should note that C&J is an emerging minutia descriptor that uses deep learning, which has opened the door to new research topics in the area of latent fingerprint identification. Therefore, new minutia descriptors based on deep learning could reduce the gap between latent fingerprint identification and fingerprint verification in terms of their respective error rates in the near future.

V. CONCLUSIONS

From our review, we found that minutia descriptors are the most widely used fingerprint feature representations for fingerprint verification and latent fingerprint identification.

We provide a table with 50 fingerprint feature representations classified as five taxonomies, of which most (30) are minutia descriptors. We selected nine of those minutia descriptors based on their robustness to noise, brightness variation, non-linear distortion, and lack of features suffered by latent fingerprints to evaluate their performance for latent fingerprint identification. Hence, we developed an evaluation protocol to compute the identification rates of these nine minutia descriptors in the NIST SD27 database.

Our results show differences among minutia descriptors in terms of their CMC curves, indicating that the selection of the minutia descriptor might impact the performance of an AFIS. The best performance was obtained for the MCC descriptor in the NIST SD27 database. Nevertheless, the identification rates achieved by its local-matching algorithm indicate that there is large room for improvement (the identification rates were lower than 10%, 13%, and 24% for Rank-1, weighted Rank-20, and Rank-100, respectively).

Additionally, we found that a rotation difference $> \pm\pi/4$ between minutiae in the latent fingerprint and impression affects the performance of the minutia descriptors by less than 2% for Rank-1, 4% for weighted Rank-20, and 8% for Rank-100 in the NIST SD27 database.

Finally, we observed that ridge count and minutia type are suitable features for latent fingerprint identification by comparing the identification rates of the minutia descriptors proposed by Jiang and Yau and Jea and Govindaraju in our evaluation protocol. However, ridge frequency does not improve the performance for latent fingerprint identification when locally matching latent fingerprints in the NIST SD27 database, according to the identification rates of the minutia descriptors proposed by Tico and Kuosmanen and by Feng.

In future work, we recommend developing new minutia descriptors that combine fingerprint features starting from the most accurate descriptors found in these experiments and considering ridge count, minutia type, and minutia descriptors based on deep learning. Furthermore, we are working on a similar analysis for latent palm print due to the lack of analysis of the suitability of palm print representation for latent palm print identification.

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