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DOTS AND INCIPIENTS: EXTENDED FEATURES FOR PARTIAL FINGERPRINT MATCHING

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ABSTRACT

There are fundamental differences in the way fingerprints are compared by forensic examiners and current automatic systems. For example, while automatic systems focus mainly on the quantitative measures of fingerprint minutiae (ridge ending and bifurcation points), forensic examiners often analyze details of intrinsic ridge characteristics and relational information. This process, known as qualitative friction ridge analysis [1], includes examination of ridge shape, pores, dots, incipient ridges, etc. This explains the challenges that current automatic systems face in processing partial fingerprints, mostly seen in latents. The forensics and Automatic Fingerprint Identification Systems (AFIS) communities have been active in standardizing the definition of extended feature set, as well as quantifying the relevance and reliability of these features for automatic matching systems. CDEFFS (Committee to Define an Extended Feature Set) has proposed a working draft on possible definitions and representations of extended features [2]. However, benefits of utilizing these extended features in automatic systems are not yet known. While fingerprint matching technology is quite mature for matching tenprints [3], matching partial fingerprints, especially latents, still needs a lot of improvement. We propose an algorithm to extract two major Level 3 feature types, dots and incipients, based on local phase symmetry and demonstrate their effectiveness in partial print matching. Since dots and incipients can be easily encoded by forensic examiners, we believe the results of this research will have benefits to Next Generation Identification (NGI) systems.

1. INTRODUCTION

Characteristic fingerprint ridge detail is generally categorized into three levels [1], namely Level 1 (ridge flow), Level 2 (minutiae), and Level 3 (e.g., dots, incipients, ridge width and shape, pores, breaks, creases, scars). It has been established that one of the strategies and visual skills that forensic examiners develop during training is the focus on within-minutiae discrimination (Level 3) rather than between-minutiae comparison (Level 2) [4]. On the other hand, automatic systems perform primarily between-minutiae comparisons using attributes including type (ridge ending / bifurcation), location (x- and y-coordinates) and angle (between the tangent to the ridge line at the minutiae position and the horizontal axis), as defined in [5]. As a result, automatic systems often cannot match the performance of forensic examiners, especially when prints are small and contain insufficient number of minutiae, as seen mostly in latents. In fact, there is a general agreement that current automatic systems perform very well on tenprint matching [3], whereas partial or latent print matching still remains a major challenge.

Federal Bureau of Investigation (FBI) is conducting a study for Next Generation Identification Technologies (NGI), which aims to upgrade the current IAFIS systems for higher identification accuracy and efficiency, especially to improve latent matching capability. At the same time, CDEFFS (Committee to Define an Extended Feature Set) has released a working draft standard for extended features that can be potentially encoded and used by both forensic examiners and automatic systems [2]. Among the proposed Level 3 (minor) features, pores have been most extensively evaluated for automatic extraction and matching [6, 7, 8, 9]. However, these features often require high resolution and good quality fingerprints. In fact, a recent survey [10] of latent practitioners revealed that dots, scars, warts have the most evidential value and are reproducible, while pores and ridge width are not. As a result, we propose to evaluate automatic extraction of dots and incipients for 500ppi partial print matching.

2. DOTS AND INCIPIENTS

Human fingers are known to display friction ridge skin (FRS) that consists of a series of ridges and furrows, generally referred to as fingerprints. It has been suggested that friction ridges are composed of small "ridge units", and the number of ridge units and their locations are randomly established. As a result, the shape, size, alignment of ridge units and their fusion with an adjacent ridge unit are unique for each person (see figure 1). Occasionally, a ridge unit may stay isolated that looks like a *dot* between normal ridges (see red arrows in figure 1(b)). In addition, thin and often fragmented ridges may also appear between normal ridges, known as *incipients* (see blue arrows in figure 1(b)).

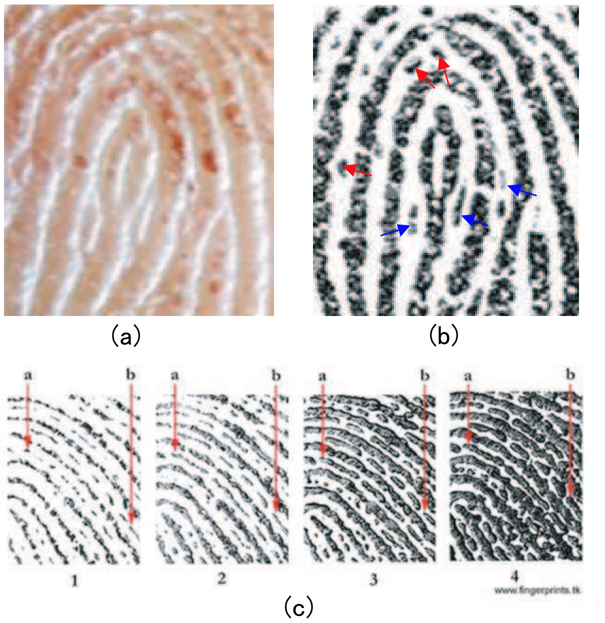


Fig. 1. Dot and incipients in (a) a friction skin image and (b) a corresponding fingerprint impression. The appearance of incipients can be significantly affected when pressure increases in the four impressions in (c) [11].

Unlike dots, which are normal ridge units, incipients are normal forming units that remained "immature" at the time of differentiation when primary ridge formation stopped. An incipient is often much thinner than a dot, yet its appearance can be significantly affected by pressure, as show in figure 1(c). This often makes it difficult for machines to distinguish a dot and an incipient. For this reason, in our extraction algorithm, we do not distinguish the two feature types.

It has been reported that incipients are observed in about 45% of the people and 13.5% of the fingers [11]. Dots and incipients have been found to be particularly distinctive with high density in small areas, which can be very helpful for partial (latent) print identification, as shown in figure 2.

3. FEATURE EXTRACTION

Generally, features at all three levels in a fingerprint are mutually correlated. For example, minutiae points can be extracted from the skeletonized ridge map; ridge path deviations correlate with the surrounding ridge formations; dots and incipients only occur between normal friction ridges; pore distribution naturally follows the ridge structure and appears only on ridges, not valleys [1, 6]. In fact, it is known that forensic examiners view fingerprints with a context-related effect

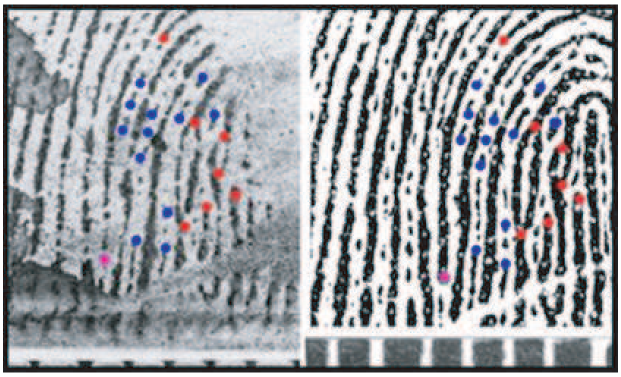


Fig. 2. Incipients (blue) are useful in combination with minutiae (red) to establish identification between (a) a latent and (b) the corresponding tenprint impression [11].

in which the perception of one feature is influenced by the presence or absence of other features [4]. As a result, our extraction algorithm for dots and incipients is designed based on ridge information and local orientation fields. Figure 3 demonstrates the overall extraction process.

The key component of our extraction algorithm is to estimate the local phase symmetry for ridge pixels. Because dots and incipients are isolated (short or thin ridge formations between normal ridges), they present slightly higher local symmetry than normal ridges. As a result, we employ wavelets based on complex valued Log Gabor functions to measure the local phase symmetry [12], as described below.

Let I denote a fingerprint image, and M_n^e and M_n^o denote the even-symmetric (*cosine*) and odd-symmetric (*sine*) wavelets at scale n. We can obtain the symmetry/asymmetry responses by convolving I at pixel (x,y) with each quadrature pair of filters, given by

$$[e_n(x,y), o_n(x,y)] = [I(x,y) * M_n^e, I(x,y) * M_n^o]. \quad (1)$$

The amplitude of the transform at scale n is defined as

$$A_n(x,y) = \sqrt{(e_n^2(x,y) + o_n^2(x,y))} \quad (2)$$

and the phase is defined as

$$\phi_n(x,y) = \arctan(e_n^2(x,y), o_n^2(x,y)). \quad (3)$$

At a point of symmetry, we would expect the absolute value of the even-symmetric filter outputs to be large and the absolute value of the odd-symmetric filter outputs to be small. Filters with multiple scales are applied and a weighted average of the filter responses over multiple scales is formed. The symmetry value is defined as the normalized difference of the absolute value between outputs from even-symmetric and odd-symmetric filters, given by

$$\begin{aligned} Sym(x,y) &= \frac{\sum_n \lfloor A_n(x,y)[|cos(\phi_n(x,y))| - |sin(\phi_n(x,y))|]\rfloor}{\sum_n A_n(x,y)} \quad (4)\\ &= \frac{\sum_n \lfloor[|e_n(x,y)| - |o_n(x,y)|]\rfloor}{\sum_n A_n(x,y)}. \quad (5)\end{aligned}$$

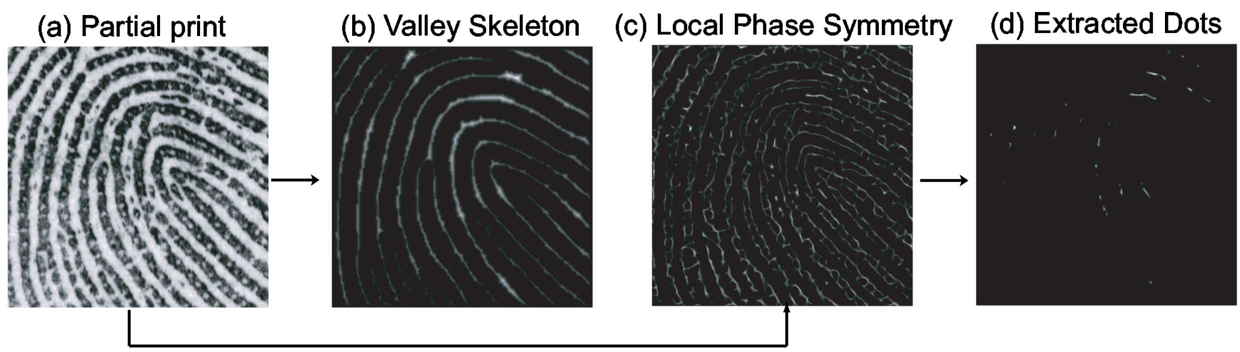


Fig. 3. The extraction procedure for dots and incipients.

Once local symmetry is estimated, it is multiplied with the skeletonized valley image. This is because dots and incipient ridges only occur in valleys between normal friction ridges. Instead of the traditional one-pixel wide binary skeletonization, we obtain the continuous skeletonization based on Level Sets, proposed in [13]. Empirically determined thresholding is finally applied to the resulting image and centroids of connected components are recorded as positions of dots and incipients. Orientations of dots are also estimated based on local orientation fields. Figure 3(e) shows the locations of extracted dots and incipients (in red).

4. MATCHING

A commercial minutiae-based matcher Neurotechnologija VeriFinger 4.2 [14] is used to obtain the alignment between the partial print and the full print, and a match score S_m based on minutiae features is also computed. Then, minutiae templates of both sample and test images are modified by importing the centroids of the extracted dots and incipients together with attributes including position, direction and type ("ending"). The modified templates are once again sent to the matcher and a new match score S_d based on the original alignment is computed. Note dots will be used to establish alignment when minutiae is not available in the partial prints. To obtain the best performance, we fuse the two scores using the sum-rule. Because the two scores are generated from the same matcher and highly correlated, there is no need for score normalization.

5. EXPERIMENTAL RESULTS

The goal of this study is to investigate how extended features can be utilized in automatic systems for improving latent search capability and accuracy. To our knowledge, there is no public domain database that contains latents with extended features encoded by forensic examiners. As a result, the NIST special database 30 (dual resolution tenprints) is used in our experiment for performance evaluation [15]. This database includes 72 tenprint cards from 36 users, 10 fingers per user and 2 impressions per finger, scanned at both 500ppi and 1000ppi.

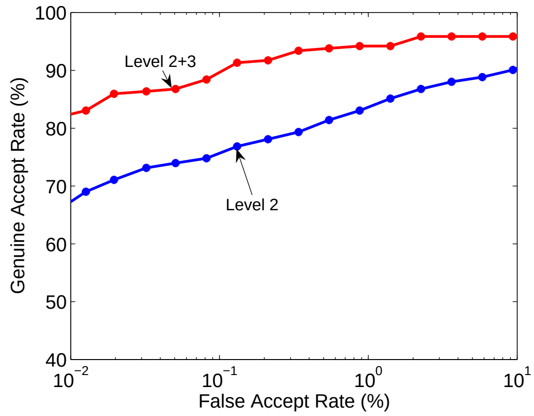
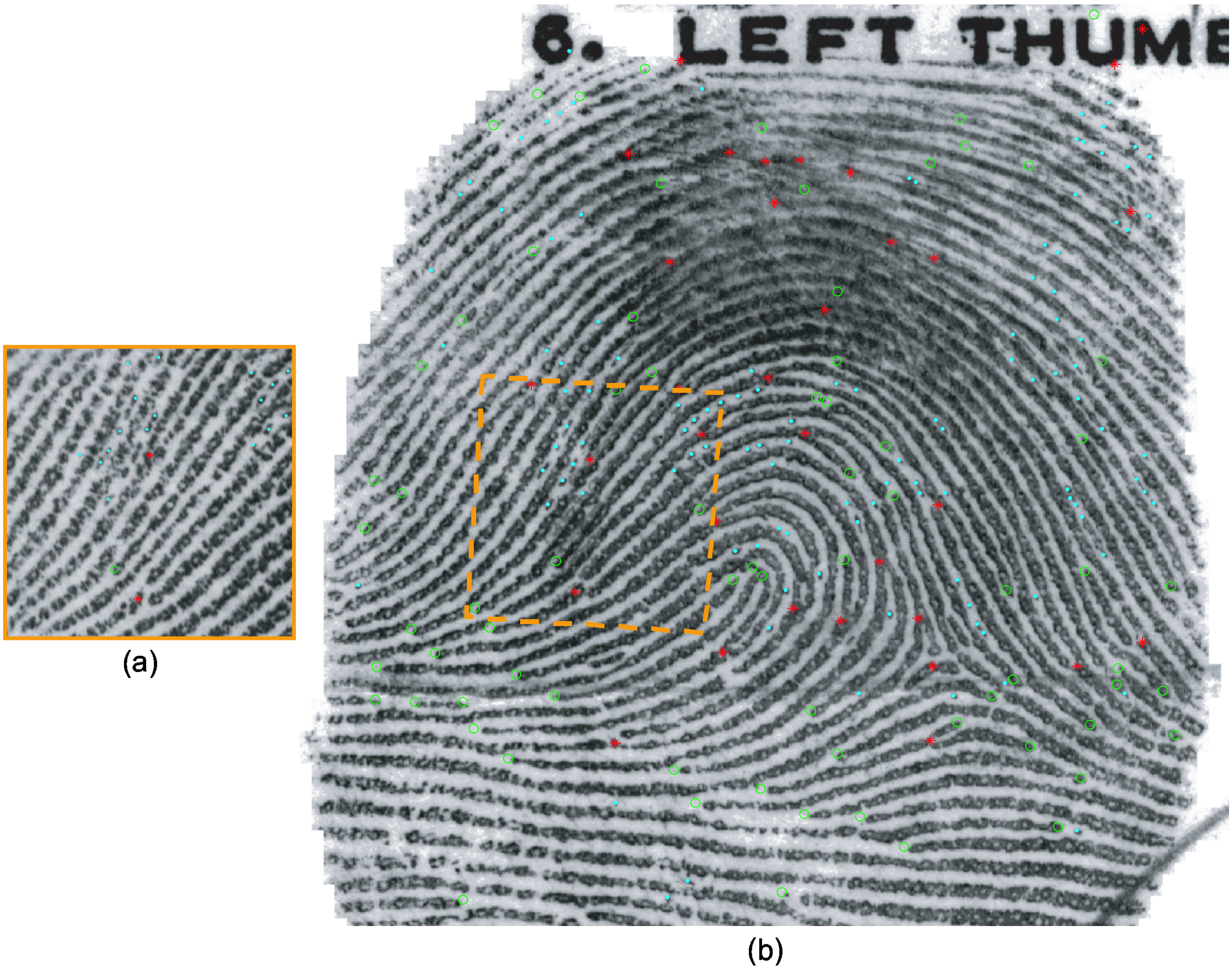


Fig. 5. Comparison of the partial-to-full tenprint matching performance (ROC curves) using Level 2 features only (blue lines) and Level 2 features in combination with Level 3 features (red lines). The partial prints are manually generated.

To simulate the partial-to-full matching, we conduct two experiments. In the first experiment, we manually crop partial prints (300×300 pixels in size) from the first impression of each finger (242 images) and match them against the full print ($\sim 1500 \times 1500$ pixels in size) of the second impression of all fingers (360 images) at 1000 ppi. This results in a total number of 242 genuine matches and 86,878 impostor matches. Figure 4 demonstrates the feature extraction and matching of a genuine partial-full pair. The square region marked by the dashed line in figure 4(b) is found in correspondence with the partial print in figure 4(a). Note the dots and incipients extracted using the proposed method are shown in blue, whereas minutiae extracted using the Neurotechnologija matcher are



(a) (b)

Fig. 4. Dots / incipients (blue) and minutiae points (red and green) are extracted and shown in (a) a partial fingerprint and (b) a full print that contains the corresponding region in dashed line. The match score has been increased from 30 (S_m) to 388 (S_d) after dots are encoded in the template.

shown in red (bifurcation) and green (ending). As we can see, the number of feature points in the partial fingerprint in figure 4(a) and the corresponding region in figure 4(b) increase from 3 to 20 and 7 to 24, respectively, after dots are encoded in the templates. Figure 5 shows the matching results with and without using the dots and incipients. Significantly higher matching accuracy is achieved after dots and incipients are utilized.

However, in the first experiment, the manual cropping ensures that the partial fingerprints are of reasonable quality and contain significant number of dots / incipients (14.7 in average). This is usually not the case in practice. As the result, we conduct the second experiment by randomly cropping 10 partial prints from the first impression to generate a total of 3600 partial images and matched them against the second full impression (360 images). For computational efficiency, 20% of partial prints (two each finger) are used for impostor score generation. This results in a total number of 3,600 genuine matches and 258,480 impostor matches. Because the cropping is completely random, the partial prints can be from any part of the full fingerprint. As a result, these partial prints differ significantly in quality, and the number of minutia and dots / incipients contained. In fact, only 75% of the partial prints have dots / incipients extracted. Figures 6 and 7 show the distribution of the number of minutiae and dots / incipients, respectively, extracted from the 3,600 partial prints. The max, min and median number of minutiae (dots / incipients) are 26 (40), 0 (0) and 8 (2). Note that in order to demonstrate the advantage of dots and incipients over other Level 3 features, which usually require high image resolution, we perform dot / incipient extraction in the second experiment at 500ppi.

In order to better analyze the results from the second experiment, we first divide the 3,600 partial prints into three

Table 1. Equal Error Rates (EER) of (a) Level 2 and (b) Level 2+3 matching for partial prints with various number of minutiae and dots / incipients. Note the number of minutiae and dots/incipients are carefully selected so that data can be as evenly distributed into 9 different groups as possible.

Partial prints with	$\leq$ 4 Minutia	5-8 Minutia	$\geq$ 9 Minutia	All
$\leq$ 2 Dots/Incipients	(a) 0.318 (b) 0.280	(a) 0.173 (b) 0.163	(a) 0.132 (b) 0.123	(a) 0.201 (b) 0.201
3-6 Dots/Incipients	(a) 0.374 (b) 0.289	(a) 0.198 (b) 0.181	(a) 0.156 (b) 0.141	(a) 0.238 (b) 0.214
$\geq$ 7 Dots/Incipients	(a) 0.337 (b) 0.114	(a) 0.184 (b) 0.124	(a) 0.223 (b) 0.154	(a) 0.231 (b) 0.167
All	(a) 0.342 (b) 0.294	(a) 0.184 (b) 0.168	(a) 0.145 (b) 0.141	(a) 0.222 (b) 0.195

groups based on the number of minutiae contained, namely (i) $\leq$ 4 minutiae, (ii) between 5-8 minutiae and (iii) $\geq$ 9 minutiae. Then for each group, we generate a pair of ROC curves by matching the partial prints with all the full prints using a) minutiae only and b) minutiae in combination with dots and incipients, as shown in figure 8. As we can see, the largest performance gain of using dots and incipients is achieved when the partial prints have small number ($\leq$ 4) of minutiae. This improvement becomes less significant as the number of minutiae in the partial prints increases. This is consistent with the generally agreed notion that Level 3 features help improve the matching performance, particularly when the number of minutiae is small.

Further, we divide each group of partial prints into another three groups with regards to the number of dots / incipients extracted. This results in a total of 9 partial print groups and again, each group is matched against all full prints and the EERs for each group using (a) minutiae only and (b) minutiae in combination with dots / incipients are shown in Table 1. The table shows that matching using dots / incipients in combination with minutiae improves the performance in almost all scenarios, especially when the number of dots / incipients is large ($\geq$ 7). Note the ROC curves shown in figure 8 correspond to the matching results shown in the last row in Table 1.

Both of our experiments show that dots / incipients provide discriminative information and when combined with minutiae, can help improve the system performance. However, this improvement is subject to image quality and the number of Level 2 and Level 3 features available.

6. CONCLUSIONS AND FUTURE WORK

We have presented an automatic algorithm to extract and utilize extended features, namely, dots and incipients, for partial-to-full fingerprint matching at both 500ppi and 1000ppi. To robustly detect these extended features, we introduce a contrast-invariant local phase symmetry measure. We also show that the encoding of extracted features (dots and incipients) are consistent with the newly proposed CDEFFS standard [2]. Our experimental results demonstrate that dots and incipients can be automatically extracted and, and when combined with minutiae, can improve the matching performance, especially when the number of minutiae is small or the number of dots/ incipients is large. Since dots and incipients can be easily encoded by forensic examiners, we believe the results of this research will have benefits in Next Generation Identification Needs (NGI) systems.

This study is our first step to evaluate the benefits of extended feature set for partial print matching. We are in the process of obtaining latent database with extended features marked by forensic examiners, so that we can better evaluate our approach. We also plan to integrate our previous work on pores and ridge contours with this work. We believe further research on extended features will not only improve the effectiveness of latent encoding and identification, but also provide insight into the fundamental issues of fingerprint permanence and individuality.

Acknowledgment

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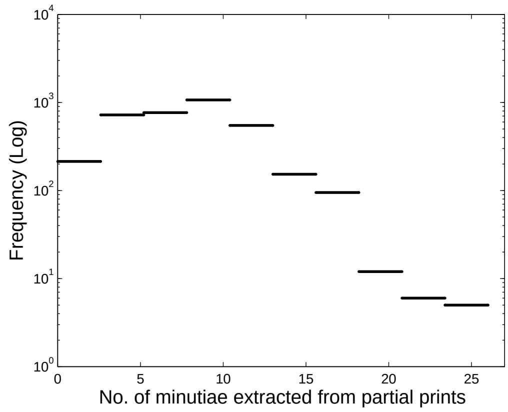

Fig. 6. Distribution of the number of extracted minutiae from the 3,600 partial prints.

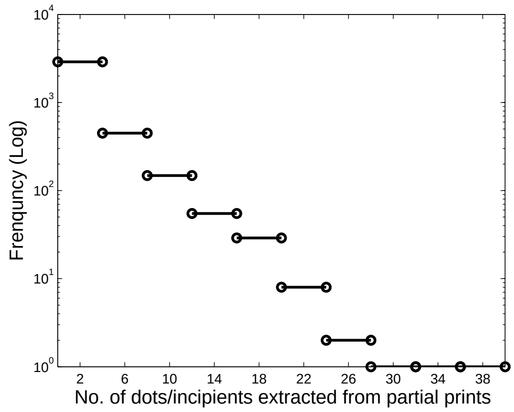

Fig. 7. Distribution of the number of extracted dots / incipients from the 3,600 partial prints.

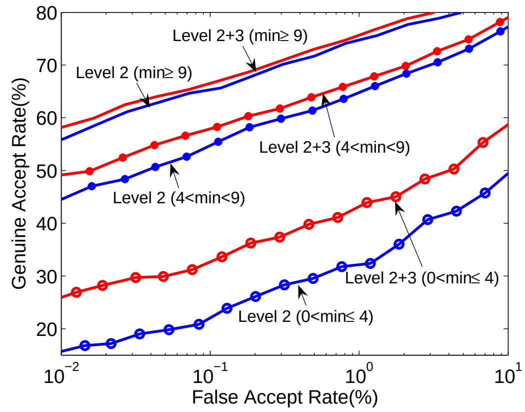

Fig. 8. Comparison of the partial-to-full tenprint matching performance (ROC curves) using Level 2 features only (blue lines) and Level 2 features in combination with Level 3 features (red lines). The partial prints are randomly generated and divided into three group with various number of minutiae ((i) ≤ 4, (ii) between 5-8 and (iii) ≥ 9) to generate three pairs of ROC curves. The number of genuine (impostor) comparisons for each of the three groups are 635 (47,485), 1,512 (115,948) and 1,453 (95,047), respectively.

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