Latent Fingerprint Matching using Descriptor-Based Hough Transform

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Abstract

Identifying suspects based on impressions of fingers lifted from crime scenes (latent prints) is extremely important to law enforcement agencies. Latents are usually partial fingerprints with small area, contain nonlinear distortion, and are usually smudgy and blurred. Due to some of these characteristics, they have a significantly smaller number of minutiae points (one of the most important features in fingerprint matching) and therefore it can be extremely difficult to automatically match latents to plain or rolled fingerprints that are stored in law enforcement databases. Our goal is to develop a latent matching algorithm that uses only minutiae information. The proposed approach consists of following three modules: (i) align two sets of minutiae by using a descriptor-based Hough Transform; (ii) establish the correspondences between minutiae; and (iii) compute a similarity score. Experimental results on NIST SD27 show that the proposed algorithm outperforms a commercial fingerprint matcher.

1. Introduction

The practice of using latent fingerprint for identifying suspects is not new. According to Cummins and Midlo [2], the first publication in modern literature related to fingerprint identification appeared in *Nature*, in 1880. This publication was entitled "On the Skin-furrows of the Hand," authored by Faulds [3]. In this article, Faulds suggested that fingerprints left on crime scenes could be used to identify criminals or to exclude suspects. Soon after this article was published, a letter written by Herschel was published in *Nature* [5] stating that he had been using fingerprint as a method of identification in India for about 20 years, with different applications such as to avoid personification.

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(a) (b) (c)

Figure 1. Types of Fingerprints obtained by different acquisition methods. (a) Rolled (ink) (NIST SD27), (b) plain (live-scan) (FVC2002), and (c) latent (NIST SD27).

In 1893, the acceptance of the hypothesis by the Home Ministry Office, UK, that any two individuals have different fingerprints made many law enforcement agencies aware of the potential of using fingerprints as a mean of identification [8]. Some law enforcement agencies started collecting fingerprints from offenders so that they could identify them later in case they changed their names to evade harsher penalties. Also, fingerprints collected from crime scenes were compared to fingerprints collected from previous offenders so that they could identify repeat offenders, criminals who have been previously arrested.

Fingerprint identification started as a completely manual approach. Due to growing demands on fingerprint recognition, research was initiated to automate fingerprint recognition, which led to the development of *Automated Fingerprint Identification Systems* (AFIS).These systems are used worldwide not only by law enforcement agencies but also in many other government and commercial applications. Nowadays fingerprint recognition is routinely used in civilian applications that have stringent security requirements.

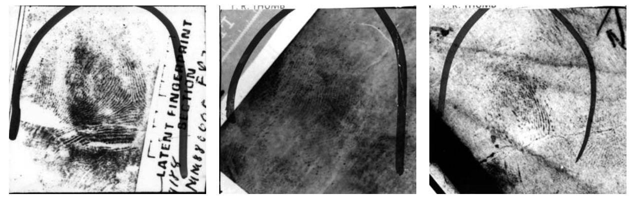
There are three types of fingerprints: rolled, which is a print obtained by rolling the finger "nail-to-nail" on a paper or the platen of a scanner; plain, which is a print obtained by placing the finger flat on a paper or the platen of a scanner without rolling; and latents, which are lifted from surfaces of objects that are inadvertently touched or handled by a person typically at crime scenes (see Fig. 1). Lifting of latents may involve a complicated process, and it can range from simply photographing the print to more complex dusting or chemical processing.

Rolled prints contain the largest amount of information about the fingerprint since they contain information from nail-to-nail; latents usually contain the least amount of information for matching or identification. Compared to rolled or plain fingerprints, latents are smudgy and blurred, capture only a small finger area, and have large nonlinear distortion due to pressure variations. Due to their poor quality and small area, latents have a significantly smaller number of minutiae compared to rolled or plain prints (the average number of minutiae in NIST Special Database 27 (NIST SD27) [12] images is 21 for latents versus 106 for the corresponding rolled prints). Those characteristics make the latent fingerprint matching problem very challenging.

Manual latent fingerprint identification is performed following a procedure referred to as ACE-V (analysis, comparison, evaluation and verification) and it requires a large amount of human intervention. Because this procedure is quite tedious and time consuming for latent examiners, latents are usually matched against full prints of a small number of suspects identified by other means. With the invention of AFIS, fingerprint examiners identify latents using a semi-automatic procedure that consists of following stages: (i) manually mark the features (minutiae and singular points) in the latent, (ii) launch an AFIS search, and (iii) visually verify each of the candidate fingerprints returned by AFIS. The accuracy and speed of this procedure is still not satisfactory.

Recent studies on latent fingerprints can be classified into two categories according to their objective: higher matching accuracy [4, 6, 7] or higher degree of automation [15, 13]. Improved latent matching accuracy has been reported by using extended features which are manually marked for latents [6, 7]. However, marking extended features (orientation field, ridge skeleton, etc.) in poor quality latents is very time-consuming and might be only feasible in rare cases.

NIST has been conducting a multi-phase project on Evaluation of Latent Fingerprint Technologies (ELFT) to evaluate automatic latent feature extraction and matching techniques [10]. In Phase I, the most accurate system showed a rank-1 accuracy of 80% (100 latents against $10,000$ rolled prints). In Phase II, the rank-1 accuracy of the most accurate system was 97.2% (835 latents against $100,000$ rolled prints). These accuracies cannot be directly compared since the Phase I and Phase II evaluations used different databases. Also, the quality of latents used in Phase II is better compared to Phase I. Fig. 2 shows three latents of different quality in NIST SD27. The impressive matching accuracy reported in ELFT does not mean that the current



(a) (b) (c)

Figure 2. Latent fingerprints of three different quality levels in NIST SD27. (a) Good, (b) Bad, and (c) Ugly.

practice of manually marking minutiae in latents should be changed.

The goal of this work is to develop a latent fingerprint matching algorithm that is solely based on minutiae. Since manually marking minutiae in latents is a common practice in the latent fingerprint community, the proposed matcher can be directly used in operational settings.

The rest of the paper is organized as follows: in Section 2, all steps of our proposed method are described; in Section 3, our experimental results are presented and discussed; in Section 4, we present our conclusions and future work.

2. Latent Matching Approach

There are three main steps in fingerprint matching: alignment (or registration) of the fingerprints, pairing of the minutiae, and score computation. In our approach, we use a Descriptor-based Hough Transform to align two fingerprints. Given two sets of aligned minutiae, two minutiae are considered as a matched pair if their Euclidean distance and direction difference are less than pre-specified thresholds. Finally, a score is computed based on a variety of factors such as the number of matched minutiae and the similarity between the descriptors of the matched minutiae pairs. Figure 3[1] shows an overview of the proposed approach. It is important to emphasize that while latents are manually encoded (namely marking minutiae), minutiae in rolled prints are automatically extracted.

2.1. Local Minutia Descriptor

Minutia Cylinder-Code (MCC) is a minutiae representation based on 3D data structures [1]. In the MCC representation, a local structure is associated to each minutia. This local structure is represented as a cylinder, which contains information about the relationship between a minutia and its neighboring minutiae. The base of the cylinder is related to the spatial relationship, and its height is related to the directional relationship. Each cell in the cylinder accumulates contributions from each minutia in the neighborhood. The resulting cylinder can be viewed as a vector, and therefore the similarity between two minutia descriptors can be easily

[1]Local minutia descriptors shown in Figure 3 is from [1].

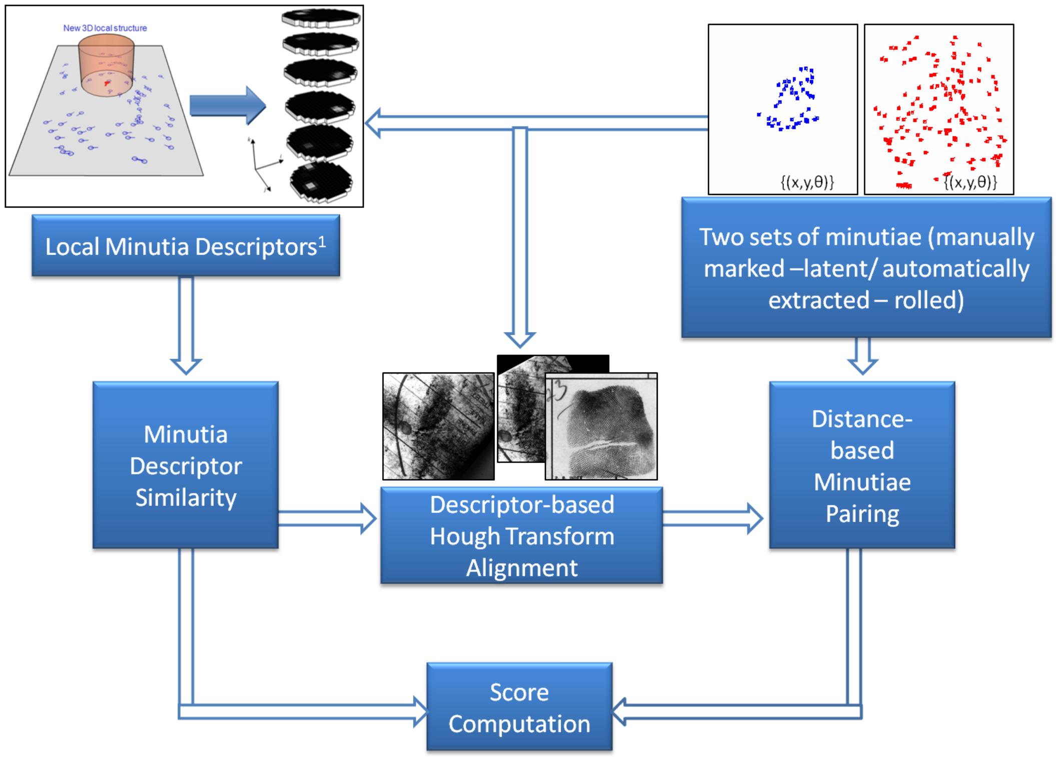


Figure 3. Overview of the proposed approach.

computed as a vector correlation measure. A more detailed description of the cylinder generation and of the similarity between two cylinders can be found in [1]. This representation presents some advantages, such as: invariant to translation and rotation; robust against small skin distortion and missing or spurious minutiae; and of fixed length.

2.2. Fingerprint Alignment

Fingerprint alignment or registration consists of estimating the parameters (rotation, translation and scale) that align two fingerprints. There are a number of features that may be used to estimate alignment parameters between two fingerprints, including orientation field, ridges and minutiae. There are also a number of ways of aligning two fingerprints: Generalized Hough Transform, local descriptors, energy minimization, etc.

In the latent fingerprint case, singularities are not always present, making it difficult to base the alignment of the fingerprint on singular points alone. To obtain manually marked orientation field is expensive, and to automatically extract orientation field from a latent image is a very challenging problem. Since manually marking minutiae is a common practice for latent matching, our approach to align two fingerprints is based on minutiae.

Ratha *et al.* introduced an alignment method for minutiae matching that estimates rotation, scale, and translation parameters using a Generalized Hough Transform [14]. Given two sets of points (minutiae), a matching score is computed for each transformation in the discretized set of all allowed transformations. For each pair of minutiae, one minutia from each set, and for given scale and rotation parameters, unique translation parameters can be computed. Each parameter receives "a vote" proportional to the matching score for the corresponding transformation. The transformation that gives the maximum score is considered the best one. In our approach, the alignment is conducted in a very similar way, but the evidence for each parameter is accumulated based on the similarity between the local descriptors of the two involved minutiae, with the similarity and descriptor being the ones described in Section 2.1.

Given two sets of minutiae, one from the latent and the other from the rolled print being compared, translation and rotation parameters can be obtained for each possible minutiae pair (one minutia from each set). Let $\{(x_l, y_l, \theta_l)\}$ and $\{(x_r, y_r, \theta_r)\}$ be the minutiae sets for latent and rolled prints, respectively, centered at their means. Then, for each pair of minutiae, we have

$$\theta = \min\left(\|\theta_l - \theta_r\|, 360 - \|\theta_l - \theta_r\|\right), \quad (1)$$

$$\begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} = \begin{pmatrix} x_r \\ y_r \end{pmatrix} - \begin{pmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} x_l \\ y_l \end{pmatrix}. \quad (2)$$

Since it is not necessary to consider the scale parameter in fingerprint matching, unique translation parameters can be obtained for each pair based on the rotation difference between the minutiae in the pair. The translation and rotation parameters need to be quantized to the closest bins. After the quantization, evidence is accumulated in the correspondent bin based on the similarity between the local minutiae descriptors. The assumption here is that true mated minutiae pairs will vote for very similar sets of alignment parameters, while non-mated minutiae pairs will vote randomly throughout the parameter space. As a result, the set of parameters that presents the highest evidence is considered the best one. For robustness, more than one set of alignment parameters with high evidence are considered.

In order to make the alignment computationally efficient and also more accurate, we use a two-stage approach for the Descriptor-based Hough Transform. We first perform the voting in a relatively coarse parameter space. Based on the peaks in the Hough space, we repeat the voting inside a neighborhood around the peaks, but with a more refined set of parameter range. We also keep track of the points that contribute to the peaks and then compute a rigid transformation matrix from those points.

2.3. Minutiae Pairing

After aligning two sets of minutiae, we need to find the minutiae correspondences between the two sets, i.e. minutiae need to be paired. The pairing of minutiae consists of finding minutiae that are sufficiently close in terms of location and direction. Let $m_i = (x_i, y_i, \theta_i)$ be a minutia from the aligned latent and $m_j = (x_j, y_j, \theta_j)$ be a minutia from the rolled print. Then, m_i and m_j are considered paired or matched minutiae if

$$d(m_i, m_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq d_0 \qquad (3)$$

$$\theta_{ij} = \min\left(\|\theta_i - \theta_j\|, 360 - \|\theta_i - \theta_j\|\right) \leq \theta_0, \qquad (4)$$

In aligning two sets of minutiae, this is the most natural way of pairing minutiae. We use a one-to-one matching, which means each minutia in the latent can be matched to only one minutia in the rolled print. Ties are broken based on the closest minutia.

2.4. Score Computation

Score computation is a very important step in the matching process. A straightforward approach to compute the matching score consists of the number of matched minutiae divided by the average number of minutiae in the two fingerprints. This is not appropriate for latent matching because the number of minutiae in different latents varies substantially. One solution to modify the above scoring method is to divide the number of matched minutiae by the number of minutiae in the latent, which is almost always smaller than the number of minutiae in the rolled print.

In our approach, we use minutiae similarity to weigh the contribution of each pair of matched minutiae. Given a search fingerprint (latent) and a template fingerprint (rolled), and considering that the fingerprints are already aligned, let M be the set of n matched minutiae pairs between the two fingerprints, $\{m_i\}_{i=1}^{n}$ be matched minutiae pairs in M, $\{S_i\}_{i=1}^{n}$ be their respective similarities, and N be the number of minutiae in the latent. Then, the matching score between the two aligned fingerprints is given by:

$$score = \frac{\sum_{\forall m_i \in M} S_i}{N}. \qquad (5)$$

To further improve the matching performance, we combine the scores based on matched minutiae from two different pairing thresholds by their weighted sum; we assume equal weights. Since we perform 10 different alignments, we compute 10 different matching scores between two fingerprints; the final score between the two fingerprints is the maximum among the 10 scores computed from different hypothesized alignments.

3. Experimental Results

Matching experiments were conducted on the NIST Special Database 27, which consists of 258 latent fingerprint images. The background database consists of 258 mated rolled prints from NIST SD27, and the first 2,000 rolled impressions from NIST SD14 [11]. So, the total number of background prints is 2,258. NIST SD27 contains latent prints of three different qualities, termed "good", "bad", and "ugly", which were classified by latent examiners. Some examples of latents from those three qualities are shown in Fig. 2. Although this classification of latent prints as "good", "bad", and "ugly" is subjective, it has been shown that such a classification is correlated with the matching performance [6].

Another indicator of fingerprint quality that affects the matching performance is the number of minutiae in the latent print [6]. Based on the number of minutiae n in latents in NIST SD 27, Jain and Feng [6] classified latents in NIST SD 27 into three groups: large ($n > 21$), medium ($13 < n < 22$), and small ($n \leq 13$), containing 86, 85, and 87 prints, respectively. We present our experimental results for each of the six quality groups. We also show results of the commercial matcher VeriFinger [9] for the purpose of performance comparison. Although VeriFinger was not designed specifically for latent matching case, it should be noted that there is no latent fingerprint matcher SDK nor forensic AFIS available for individual use. VeriFinger is widely used as a benchmark in fingerprint publications.

We use manually marked minutiae (provided with NIST SD 27) as features in latent fingerprints. For rolled fingerprint images, only minutiae are needed for matching and they are automatically extracted using VeriFinger SDK.

Minutia Cylinder Code (MCC) is used as local descriptors for minutiae. MCC parameters are set as suggested in

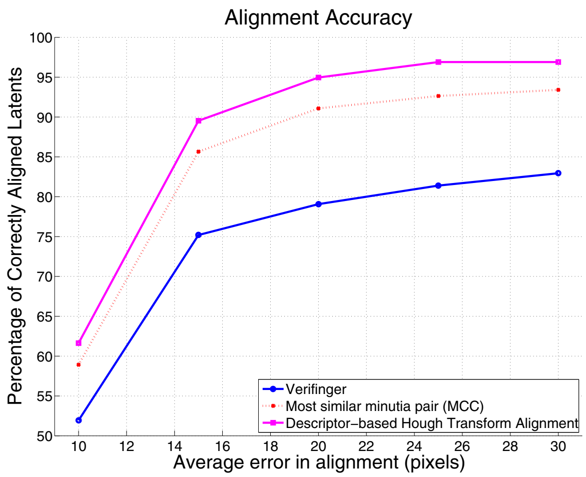


Figure 4. Alignment Accuracy: percentage of correctly aligned latents vs. alignment error.

[1], with the number of cells along the cylinder diameter as 8 (N_s). However, we consider all cells in a cylinder as valid cells. For Euclidean distance pairing, we use two different thresholds, 15 and 25 pixels, and direction difference threshold of 20 degrees.

In order to estimate the alignment error, we use ground truth mated minutiae pairs, which are marked by fingerprint examiners, to compute the average distance of the true mated pairs after alignment. If the average Euclidean distance for a given latent is less than a pre-specified number of pixels in at least one of the ten best alignments (peaks of the DBHT), then we consider it a correct alignment. This performance is shown in Figure 4. The x-axis shows the alignment error, and the y-axis shows the percentage of correctly aligned latent fingerprints in at least one of the ten alignments. For comparison, we also show VeriFinger alignment accuracy, as well as the accuracy of aligning the minutiae sets based on the most similar minutiae pair (according to the MCC similarity) - in this case, each alignment is based on one of the ten most similar minutiae pairs.

There are very few errors in alignment if we consider the average alignment error of less than 25 pixels. The main reason for these failure cases is there are a very small number of true mated minutia pairs in the overlapping area between the latent and mated rolled print, so there are not many true mated pairs voting for the correct alignment parameters. The absence of true mated pairs is due to limited number of minutiae in latents and the poor quality region in the rolled print. One such example is shown in Fig. 5. Blue squares are manually marked minutiae in the latent print (left) and automatically extracted minutiae in the rolled print (right). Red triangles indicate ground truth minutiae pairs, and the yellow lines indicate true mated pairs.

Although the minutiae pairing based on Euclidean distance and direction difference is relatively simple, it works well after the fingerprints are aligned using the Descriptor-based Hough Transform. Our approach performs better than the commercial matcher VeriFinger on manually marked minutiae; performance of both these matchers are shown in Fig. 6. We also show our results for latents of six different quality levels (good, bad, ugly; large, medium, small) separately. The rank-1 accuracies for the proposed matcher and VeriFinger are shown in Table 1 for the three subjective qualities and Table 2 for the three objective qualities.

Figure 6 shows that the advantage of our algorithm over the commercial matcher is consistent throughout the matching ranks. We can also notice that the improvement is more clearly observed on latents of poor quality and with small number of minutiae. The improvement of the proposed matcher over VeriFinger at rank-1 accuracy varies from 2.3% for latents with a large number of minutiae to 22% for latents of ugly quality. Figure 7 shows examples of latent prints of good (medium) and ugly (small) qualities correctly identified at rank-1, and Fig. 8 shows examples of latent prints incorrectly identified at higher ranks because

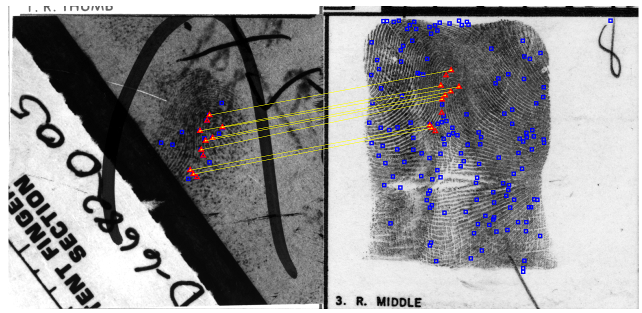


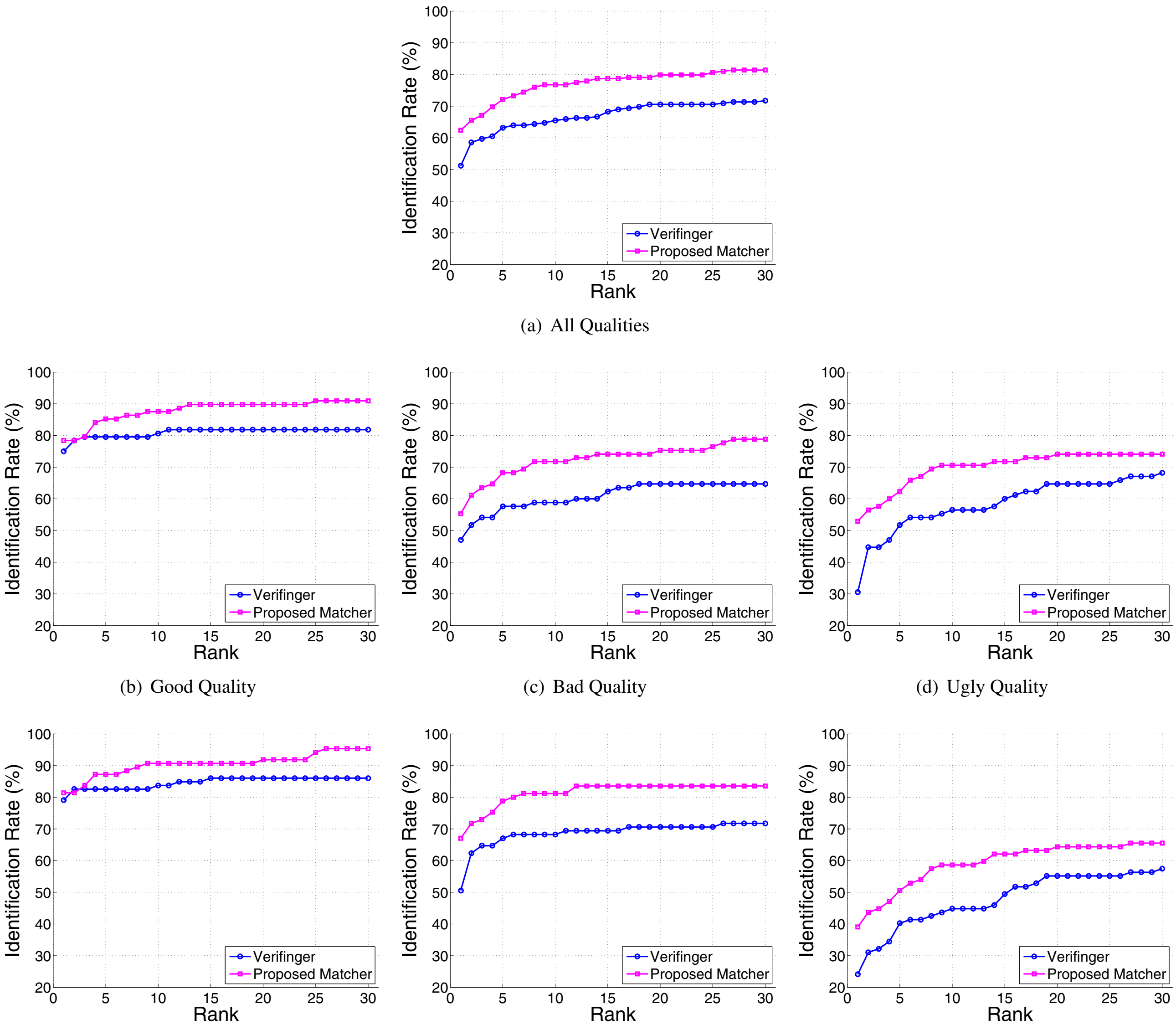
Figure 5. Example of alignment error due to the small number of true mated minutia pairs in the overlapping area between a latent and its mated rolled print.

Table 1. Rank-1 accuracies for various subjective qualities of latents in NIST SD27.

Quality	VeriFinger (%)	Proposed Matcher (%)
All	51.2	62.4
Good	75.0	78.4
Bad	47.0	55.3
Ugly	30.6	52.9

Table 2. Rank-1 accuracies for various objective qualities of latents in NIST SD27.

Quality	VeriFinger (%)	Proposed Matcher (%)
All	51.2	62.4
Large	79.0	81.4
Medium	50.6	67.0
Small	24.1	39.0



(a) All Qualities

(b) Good Quality (c) Bad Quality (d) Ugly Quality

(e) Large Quality (f) Medium Quality (g) Small Quality

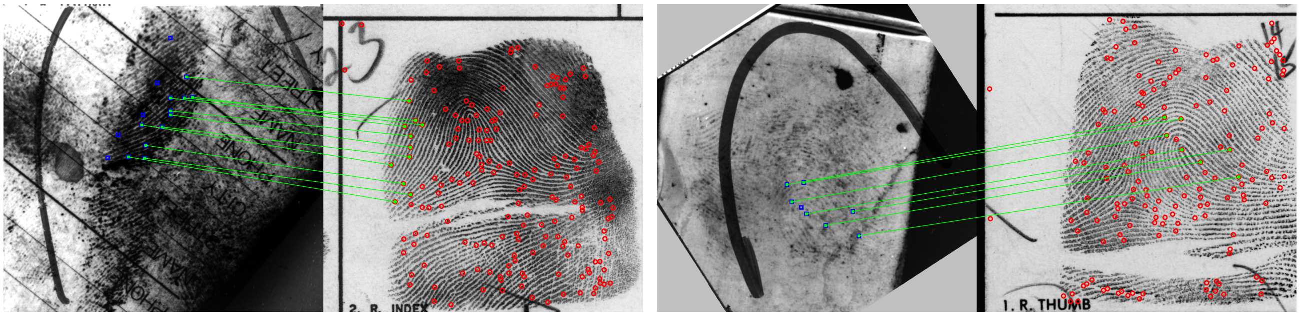
Figure 6. Overall matching performance (in terms of ROC curves) for latents with different subjective and objective qualities. Manually marked minutiae in latents are used as input for both the matchers (proposed and VeriFinger).

of the alignment errors — there are not enough matching minutiae pairs in the overlapping area between the latent and its mated rolled print.

4. Conclusions and Future Work

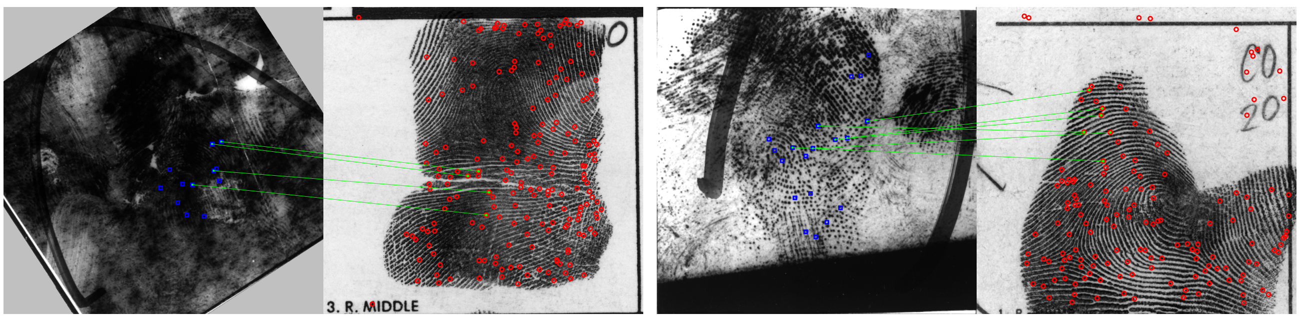
We have presented a fingerprint matching algorithm designed for matching latents to rolled/plain fingerprints. Our algorithm outperforms the commercial matcher VeriFinger over all qualities of latents in NIST SD27. The improvement in the rank-1 accuracy of the proposed algorithm over VeriFinger varies from 2.3% for latents with relatively large number of minutiae to as high as 22% for latents with the subjective quality "ugly". These results show that our matcher is more suitable for latent fingerprints.

The proposed alignment method performs very well even on latents that contain small number of minutiae. In our algorithm we take the maximum score from several hypothesized alignments based on different alignment parameters. Sometimes, the maximum score does not correspond to the correct alignment. We plan to improve the score computation by applying learning methods. Extended features manually marked by latent examiners have been shown to be beneficial for improving latent matching accuracy. We plan to incorporate extended features which are automatically extracted from the image into the current matcher to further improve the matching accuracy.



(a) (b)

Figure 7. Latent prints correctly identified at rank-1.



(a) (b)

Figure 8. Latent prints that were not successfully matched. These two latents were matched to their true mates at ranks 1253 and 1057, respectively.

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