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Pre-Registration of Latent Fingerprints based on Orientation Field

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Abstract

In this paper, we present a hierarchical algorithm to register a partial fingerprint against a full fingerprint using only the orientation fields. In the first level, we shortlist possible locations for registering the partial fingerprint in the full fingerprint using a normalized correlation measure, taking various rotations into account. As a second level, on those candidate locations, we calculate three other similarity measures. We then perform score fusion for all the estimated similarity scores to locate the final registration. By registering a partial fingerprint against a full fingerprint, we can reduce the search space of the minutiae set in the full fingerprint, thereby improving the result of partial fingerprint identification, particularly for poor quality latent fingerprints. We report the rank identification improvements of two minutiae-based automated identification systems on the NIST-SD27 database when we use our hierarchical registration as a pre-alignment.

Keywords:
Partial fingerprint, Orientation field, Pre-Registration, Minutiae matcher

1. Introduction

Any impression made by the friction ridge skin of the human finger is generally termed as fingerprint. Fingerprints which are revealed using some chemical or optical processing from a crime scene are called latent fingerprints. These are unintentionally left fingerprints found in the crime scenes. In the realm of forensic analysis (criminology), the use of latent fingerprints is a routine procedure to identify suspects. Such practice has been followed for over a century now, and has most of the time proven to be pertinent in identifying the suspects. Consequently, the identity of an individual established on the basis of fingerprints is accepted by law enforcement agencies [1] [2].

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Fingerprints are also widely used in civilian biometric recognition applications such as authentication, passport controls, biometric based digital identity, etc. Since the fingerprint is one of the oldest biometric traits, many techniques have been proposed in the literature for fingerprint recognition. It is comparatively a mature biometric trait compared against face, iris, voice, etc. Automated Fingerprint Identification Systems (AFIS) are widely used for fingerprint recognition in both forensic as well as commercial domains. Most AFIS currently use two prominent ridge characteristics (called minutiae) namely ridge-endings and bifurcations. The minutia-based decision is accepted as a proof of identity legally by courts in almost all countries around the world [1] [2].

In general, depending on the nature of the feature used by matching algorithms, fingerprint matching can be broadly classified into correlation-based matching, minutiae-based matching and non-minutiae feature-based matching. In correlation-based matching, gray scale fingerprint images of both input and reference are superimposed and pixel correlations are computed between them. In minutiae-based matching, minutiae stored as sets of points are compared using point pattern matching algorithms. In non-minutiae feature-based matching, other features of fingerprints such as orientation fields, frequency maps, ridge shapes, texture information etc, are used for matching the input and the reference [2].

Irrespective of the core methodology used for fingerprint matching, the alignment between the input and the reference fingerprint is a crucial step. This is because the fingerprint images captured in different instances might have different rotation, translation or non-linear deformation between them. The main objective of fingerprint alignment is to estimate the transformation parameters between input and reference fingerprints.

The most widely used alignment method is based on minutiae. The main idea behind minutiae-based alignment is to search in the space of transformation parameters to find an optimal transformation with the maximum number of matched minutiae between the input and the reference. One such methodology is based on the generalized Hough transform [3]. The main disadvantage for such technique is the inaccuracy in the transformation estimation due to discretization of the parameters space. Other approaches could be to use brute force to check for all possible correspondences between minutiae pairs. There exists some alignment techniques that augment minutiae with other supplementary features such as ridge information, orientation fields around a small neighborhood of minutiae, geometric relationships between minutiae and its neighbors, etc.

Alignment of full fingerprints is a well studied problem. But these methods are limited in alignment accuracy due to quantization of transformation parameters, or are not adapted for the partial fingerprint scenario. Partial fingerprints can arise in a number of situations, for example [4][5]: latent fingerprints lifted from crime scenes, due to small size of the fingerprint capturing devices, or an already enrolled fingerprint has noisy regions and is left only with a partial good/recognizable region for identification. The performance of the existing partial fingerprint identification systems mainly depends on the image quality, the number of minutiae available and other derived and extended features that can be obtained from the partial fingerprint region. Various approaches in partial fingerprint identification [5] include: the use of localized secondary features derived from relative minutia information [4], using representative points along ridge lines in addition to minutiae [6] and use of Level-3 features such as dots and incipients [7].

Most fingerprint matching algorithms in general assume approximately the same size of the minutiae set between the query and the reference minutiae for good identification accuracy [4]. It is nevertheless frequent in some scenarios to have very different sizes between query and reference due to the situations discussed above. Trying to align a partial fingerprint to a full fingerprint
only based on minutiae features could lead to errors. Law enforcement agencies employ AFIS to shortlist the suspects from its criminal database (exemplar / tenprint fingerprints). In such a scenario, it is crucial that the performance accuracy of AFIS is as good as possible. Latent fingerprints inherently are of poor quality, which leads to poor identification accuracy of AFIS in the latent scenario as compared to full fingerprint identification.

To evaluate the performance of feature extraction and matching techniques of commercial AFIS, NIST has conducted a multi-phase open project called Evaluation of Latent Fingerprint Technologies (ELFT) [8]. In Phase-I of ELFT, the best performing system reported a Rank-1 identification accuracy of 80% in which 100 latents were compared against 10,000 rolled prints [9]. In Phase-II, Evaluation-1, the best performing system reported a Rank-1 identification accuracy of 97.2% in which 835 latents were compared against 100,000 rolled prints [10], and in Phase-II, Evaluation-2, the best performing system reported a Rank-1 identification accuracy of only 63.4% in which 1,114 latents were compared against 100,000 rolled prints [11]. The reported accuracies from Phase-I and Phase-II cannot be directly compared as the database and the quality of the latents were different. In [12], it is concluded that only a limited class of latents benefits from automated procedures, and the manual procedures of marking the minutiae, determining the subjective quality of latents, etc still need to be carried out.

In this paper, we focus on the problem of aligning a partial fingerprint against a full fingerprint, especially of poor quality latents. Instead of minutiae, we used orientation fields (OF) to perform the alignment. We reduce fingerprint images to orientation images, and we look at the alignment problem as registering the partial fingerprint orientation image into the full fingerprint orientation image. Image registration is the process of overlaying (geometrically align) images of the same scene acquired in different time, different viewpoints and from different sensors [13].

Image registration is broadly classified into area-based and feature-based registration. We used area-based registration in our work. The OF representing the flow of ridges is a relatively stable global feature of fingerprint images, and it represents the intrinsic nature of the fingerprint. The representative OF of a fingerprint is very less affected by the type of capture device, contrast variations, and other quality effects compared to the input image or the minutiae. To improve the rank identification accuracy of minutiae-based matching, we consider only the minutiae around the region where the partial fingerprint orientation image is registered in the full fingerprint. This thereby reduces the search space of minutiae in the full fingerprint to approximately the size of partial fingerprint minutiae set, and consequently improves the performance of the minutiae-based matcher. A preliminary version of this work [14] [15] used correlation-based registration. Here we extent that work by incorporating a hierarchical registration method.

The main contributions of this work are as follows:

1. New correlation-based hierarchical registration method for orientation images to register a partial fingerprint in a full fingerprint.
2. Experimental exploration of various types of orientation field generation methods adequate for the registration.
3. Experimental demonstration of the performance improvement of minutiae-based matching by incorporating our registration algorithm to reduce the search space of minutiae in full fingerprints. In particular, our algorithm significantly improves the rank identification accuracy for poor quality latents (Bad and Ugly category) of NIST-SD27 database using NIST-Bozorth3 and MCC-SDK minutiae-based matchers.

In the following sections, we review related works on fingerprint orientation field based registration, describe the database used in our experiments, the similarity measures used in our
algorithm, followed by a detailed description of the proposed algorithm, experiments, results and conclusion.

2. Related works

In this section, we review the orientation field based fingerprint registration techniques in the literature, and its applicability in registering partial fingerprint images. A basic implementation of orientation-image registration requires computing the similarity between the input orientation image and the reference orientation image for every possible transformation considered between them (e.g., rotation and translation) [2]. Table 1 summarizes various techniques in the literature for orientation field based fingerprint registration together with their limitations for partial fingerprint registration.

Liu et al. [16] uses Normalized Mutual Information (NMI) as the similarity measure between orientation images to perform fingerprint registration. They align fingerprint images by maximizing NMI between the input and reference orientation images under different transformations. This technique is not suitable in aligning a partial fingerprint against full fingerprint as reported in [16]. In this approach, for good alignment, the size of input and reference orientation images should be almost of similar size. Another drawback in this technique is the necessity of enough samples of reference fingerprints to correctly estimate the distribution of the orientation field, otherwise it leads to incorrect alignment. Both of these scenarios are not pertinent in forensic fingerprint identification.

Nilsson and Bigun [17] focus on registering the fingerprints by complex filtering and by 1D projections of orientation images. Given the orientation images of the fingerprints represented as complex orientation fields, they first use specific complex filters to locate singular points (core and delta) in the fingerprint. Once these singular points are located in both input and reference orientation images, transformation parameters (rotation and translation) are estimated by superimposing the singular points. Another technique studied in [17] is 1D projections of orientation images. In this method, the fingerprint image is decomposed into 6 equally spaced directions called orientation images, and a Radon transformation is used to compute 1D projections of these orientation images (called radiograms). A translation parameter is estimated between a pair of radiograms from input and reference belonging to the same projection angle by a correlation measure. When utilizing this method, it is already assumed that the rotation alignment between input and reference is negligible or is already corrected. These techniques cannot be adapted to register partial fingerprints because singular points are not always guaranteed in partial fingerprint, and the area of overlap between input and reference is often small.

Yager and Amin [18] [19] explore three types of orientation field registration techniques summarized as follows:

1. **Distinctive Local Orientations (DLO):** This approach mainly depends on distinctive patterns in the orientation field called singular points (core and delta). This is similar to the work in [17] except for the technique to locate the singular points.

2. **Generalized Hough Transform (GHT):** In this approach, the space of all possible transformation parameters is discretized and analyzed for the best transformation.
Table 1: Summary of orientation field based fingerprint registration techniques in the literature together with their limitations to be applied for partial fingerprint registration.

<table>
<thead>
<tr>
<th>Method</th>
<th>Core technique</th>
<th>Limitations to partial fingerprint registration / latent scenario</th>
</tr>
</thead>
</table>
| Liu et al. [16]               | Maximize the Normalized Mutual Information between input and reference OF images | 1) Needs large area overlaps  
2) More reference sample required to correctly estimate OF distribution                                                                 |
| Nilsson and Bigun [17]        | 1) Singular point (SP) detection  
2) 1D radiograms                                                                   | 1) SP not guaranteed in partial or latent fingerprints  
2) Quantized projection angles, and require large area overlaps                                                                   |
| Yager and Amin [18] [19]      | 1) Distinctive Local Orientations  
2) Generalized Hough Transform  
3) Steepest Descent             | 1) SP not guaranteed in partial or latent fingerprints  
2) Needs large area overlaps                                                                                                          |

3. **Steepest Descent (SD):** Starting with some initial parameters, this algorithm evaluates a cost function. It then evaluates a sample of local neighborhood in the parameter space and selects the parameters that give greatest descent in the cost. This procedure is repeated until a local minimum has been found.

It is reported in [18] that both GHT and SD do not perform well when the area of overlap between the input and reference is small, similar to the case using NMI [16]. So, both GHT and SD are not suitable for partial fingerprint registration. Moreover, DLO looks for singular points, and it is not assured that a partial fingerprint will have singular point in it. So, all the orientation field registration techniques proposed in the literature are not suitable for partial fingerprint registration, and cannot be quickly adapted to this scenario.

3. **Database**

NIST Special Database 27 (NIST-SD27) [20] is a publicly available forensic fingerprint database which comprises of 258 latent fingerprint images, its matching tenprint images and their minutiae sets. The NIST-SD27 minutia set database is classified into two [20] [21]: 1) ideal, and 2) matched minutiae sets. The ideal minutiae set for latents was manually extracted by a forensic examiner without any prior knowledge of its corresponding tenprint image. The ideal minutiae set for tenprints was initially extracted using an AFIS, and then these minutiae were manually validated by at least two forensic examiners. The matched minutiae set contains those minutiae which are in common between the latent and its mated tenprint image. There is a one-to-one correspondence in the minutiae between the latent and its mate in the matched minutia set. This ground truth (matched minutiae set) was established manually by a forensic examiner looking at the images and the ideal minutiae.

The NIST-SD27 database consists of latent fingerprint images of varying quality. Each image is of \(800 \times 768\) pixels in size and has been scanned at 500 pixels per inch (ppi) as a gray scale image. It already contains a classification of the latent fingerprints based on the subjective quality of the image into Good, Bad and Ugly, containing 88, 85 and 85 fingerprints respectively determined by the forensic examiner. The average number of minutiae for Good, Bad and Ugly
category latents are 32, 18 and 12 respectively. Fig. 1 shows sample images from the NIST-SD27 database which belong to Good, Bad and Ugly quality categories respectively. In [22], it is shown that there is a correlation between this subjective quality classification and the matching performance.

4. Similarity measures

In this section, we introduce various similarity measures that are used in our hierarchical registration algorithm.

Let \( U \) and \( V \) be discrete images of the same size, represented as a 2D array where the array elements may represent values of gray pixel (zero-order tensors), color pixel (first-order tensors) or local directions (second-order tensors).

The Schwarz inequality:

\[
\frac{|\langle U, V \rangle|}{\|U\| \times \|V\|} \leq 1
\]

holds for \( U \) and \( V \) [23, Chapter 3]. Here, \( \langle U, V \rangle \) is the inner product between \( U \) and \( V \) calculated as :

\[
\langle U, V \rangle = \sum_{r,c} U(r,c)^* \cdot V(r,c)
\]

where \( r, c \) are the indices, \( U(r,c)^* \) is the complex conjugate of \( U(r,c) \), and \( \|U\| \) and \( \|V\| \) are the \( L_2 \) norms of \( U \) and \( V \) respectively.

The \( L_2 \) norm \( \|U\| \) is calculated as:

\[
\|U\| = \left[ \sum_{r,c} |U(r,c)|^2 \right]^{1/2}
\]

and similarly for \( \|V\| \).
The normalized correlation between \( U \) and \( V \), referred to as Schwarz Similarity (SS) hereafter is defined as:
\[
SS(U, V) = \frac{|\langle U, V \rangle|}{\|U\| \times \|V\|}
\] (4)

Because of Eq. (1), the interval for \( SS(U, V) \) is in the range \([0, 1]\). By calculating \( SS \) as a similarity measure, we can locate a given pattern (a small image) in a large image. When \( SS(U, V) \) is 1, then both \( U \) and \( V \) are viewed as most similar patterns, and when \( SS(U, V) \) is 0, they are least similar [23].

Assuming \( U \) and \( V \) represent local directions (second-order tensors) in the range \([-90°, +90°]\), we define the Manhattan-based Similarity \( MS(U, V) \) as
\[
MS(U, V) = \cos \left( \frac{1}{N} \sum_{r,c} (\Delta_{U,V}^{r,c}) \right)
\] (5)

and Euclidean-based Similarity \( ES(U, V) \) as
\[
ES(U, V) = \cos \left( \left( \frac{1}{N} \sum_{r,c} (\Delta_{U,V}^{r,c})^2 \right)^{1/2} \right)
\] (6)

where
\[
\Delta_{U,V}^{r,c} = \min (|U(r,c) - V(r,c)|, 180 - |U(r,c) - V(r,c)|)
\] (7)

which takes values in the range \([0, +90°]\) and \( N \) is the size in pixels of \( U \) or \( V \) (\( U \) and \( V \) are of same size). Because of Eq. (7), the value of \( MS \) and \( ES \) will be in the range \([0, 1]\).

The Consistency Similarity \( CS(U, V) \) (which was proposed in [24]) is defined as
\[
CS(U, V) = \frac{1}{N} \left| \sum_{r,c} e^{2i(U(r,c) - V(r,c))} \right|
\] (8)

where \( i \) is the complex number \( \sqrt{-1} \), and \(|z|\) compute the magnitude of complex number \( z \). The consistency similarity \( CS \) averages the unit vector whose phase is doubled orientation difference, and the value is in the range \([0, 1]\).

All the similarity measures \( SS, MS, ES \) and \( CS \) are in the normalized range \([0, 1]\) and these measures can be fused directly.

5. Algorithm

The algorithm to register the orientation field of the latent fingerprint with that of the tenprint fingerprint is achieved in two hierarchical levels. In the first level, we perform the normalized correlation between the OF of latent and tenprint for various rotation alignments in the range \([-45°, +45°]\) with \(1°\) increments. We then shortlist the correlation peaks for each rotation. These peaks are the possible target locations for registration.

We observed that deciding the target location only based on the normalized correlation score does not always yield satisfactory results. Therefore, a second level, on these candidate locations, we calculate \( MS, ES \) and \( CS \) similarity measures between the latent centered at the peak location
218 in the tenprint. The final registration location is chosen from the candidate locations as the one
219 that maximizes the mean similarity between \( SS, MS, ES \) and \( CS \). This gives better registration
220 accuracies than deciding only based on \( SS \). In the following section we describe this approach
221 in more detail.

5.1. Level 1: Normalized correlation

Step 1: Generate the orientation field \( L \) for the latent fingerprint and \( T \) for the tenprint finger-
222 print as detailed in Section 6. The orientations are obtained for \( 16 \times 16 \) block sizes, and are in
223 the range \( [-90^\circ, +90^\circ] \). Fig. 2(a), Fig. 2(b) shows the OF reconstructed from the minutiae set of
224 latent and tenprint respectively. The expected outcome of the registration algorithm is to locate
225 the minutiae region shown in Fig. 2(c).

Step 2: For each subregion \( T_s \) of \( T \) that is of the same size as \( L \) located at a position indexed
226 by \( s \), we can find the inner product between \( L \) and \( T_s \) as follows:

\[
(L, T_s) = \sum_{r,c} L(r,c)'^* \cdot T_s(r,c)
\]  

(9)

where \( L = e^{i2\theta_L} \), \( T = e^{i2\theta_T} \), \( i = \sqrt{-1} \), \( \theta_L \) and \( \theta_T \) are the orientation angles of \( L \) and \( T \) respectively
227 obtained from Step 1. \( L \) is the smallest rectangular region that covers the latent minutiae.

Step 3: Rotate \( L \) in the range \( [-45^\circ, +45^\circ] \) with a step size \( \Delta \theta \) of \( 1^\circ \) to compensate for rotation
228 alignment to generate \( L^\theta \). A geometric rotation of \( \Delta \theta \) implies a related rotation of the tensor field
229 of \( 2\Delta \theta \).

The correlation is obtained by generating \( (L^\theta, T_s) \) for all locations \( s \) in \( T \). The result of this
230 operation is a complex image. We then observe the correlation peaks for all \( \theta \) (magnitude of the
231 complex image). Fig. 2(d), Fig. 2(e), Fig. 2(f) shows the magnitude of the correlation images of
232 \( L^{-35^\circ}, L^{+45^\circ} \) and \( L^{+35^\circ} \) with \( T \) respectively.

Step 4: For each \( \theta \) from the correlated result, find the location of the peak \( s^\theta = (r^\theta_m, c^\theta_m) \),
233 i.e, the location with maximum magnitude in the correlated image. The peak in the correlated
234 image is where \( L^\theta \) agrees the most in \( T \). \( S = \{(r^\theta_m, c^\theta_m)\} \) is the set containing the coordinates of
235 the correlation peaks for all \( \theta \).

Step 5: For all orientations \( \theta \), calculate \( SS(L^\theta, T_m^\theta) \), where \( T_m^\theta \) is the subregion in \( T \) whose
236 center is \( s^\theta = (r^\theta_m, c^\theta_m) \). \( SS \) is the normalized correlation measure as defined in Eq. (4).

The correlation and normalized correlation are essentially equivalent in the scenario where \( \theta_L \) and \( \theta_T \) are not estimated from gray pixel gradients but reconstructed from minutiae orientations.

Consequently the orientation tensors \( e^{i2\theta_L} \) and \( e^{i2\theta_T} \) are complex numbers falling on a unit circle.

So, the magnitude of the orientation tensors thus obtained are always 1.

5.2. Level 2: Fusion of similarity scores

Step 6: For each \( s^\theta = (r^\theta_m, c^\theta_m) \in S \), calculate \( MS(L^\theta, T_m^\theta) \), \( ES(L^\theta, T_m^\theta) \) and \( CS(L^\theta, T_m^\theta) \) as
237 defined in Eq. (5), Eq. (6) and Eq. (8) respectively.
Figure 2: Various stages in the registration algorithm shown on G028L1 (latent) and G028T1 (tenprint) of NIST-SD27. (a) and (b) are the orientation field (OF) reconstructed from the ideal minutiae set, with the minutiae plotted over the OF. (c) is the region in the tenprint that is to be found after registration of (a) into (b). (d), (e) and (f) are the correlation peaks when the latent is rotated at $-35^\circ$, $1^\circ$ and $+35^\circ$ respectively and correlated with tenprint. (g) is the region where the latent pattern is identified in the tenprint based on the proposed score fusion for rotation alignment of $+1$ degree. (h) is the minutiae region selected by our pre-alignment algorithm.
Step 7: \( SS, MS, ES \) and \( CS \) are all similarity scores in the range \([0, 1]\), where 0 denotes minimum similarity and 1 denotes maximum similarity. We perform score fusion of \( SS, MS, ES \) and \( CS \) based on the mean rule, and look for the \( s^\theta = (r_m^\theta, c_m^\theta) \in S \) for which the fused similarity score is maximum.

Step 8: The resulting \( (r_m^\theta, c_m^\theta) \) is the location in the tenprint where the latent rotated at \( \theta \) is registered with best alignment (see Fig. 2(g)). The center of the latent \( L \) is registered to \( (r_m^\theta, c_m^\theta) \) in tenprint \( T \), and with a radius half the diagonal length of the bounding box of the latent orientation field, a subset of minutiae which falls inside this circular region is chosen (see Fig. 2(h)).

6. Types of Orientation Fields estimation techniques

In this study, we have used five different techniques for computing the orientation field of the fingerprints:

1. Manually estimated orientation field from the fingerprint image [25] (\textit{MANUAL\_OF}).
2. Orientation field estimated directly from fingerprint image using local Fourier analysis [26], and then performing context based correction of the OF using dictionary lookup of orientation patches [25] (\textit{DICT\_OF}).
3. Orientation field estimated directly from the fingerprint image using gradient based approach [27] (\textit{IMG\_OF}).
4. Orientation field reconstructed from the minutiae [28] (\textit{MINU\_OF}).
5. Orientation field estimated by taking the average of both of \textit{IMG\_OF} and \textit{MINU\_OF}, denoted as \textit{AVG\_OF}.

Out of these five different techniques, \textit{MANUAL\_OF} and \textit{DICT\_OF} were used for latent fingerprints, whereas \textit{DICT\_OF}, \textit{IMG\_OF}, \textit{MINU\_OF} and \textit{AVG\_OF} were used for tenprints. All the OF estimated were of 16 \( \times \) 16 block size. The region of interest for the fingerprint is considered to be the region inside the convex hull of the corresponding ideal minutiae of the fingerprint present in NIST-SD27.

7. Experiments

We perform experiments on Good, Bad and Ugly quality classifications of NIST-SD27 to report the accuracy of the proposed registration algorithm. 88 latents of Good category, 85 latents of Bad category and 85 latents of Ugly category were searched in the entire set of 258 tenprints in the NIST-SD27 database. We report the rank identification accuracy for two publicly available minutiae based matchers, namely NIST-Bozorth3 [29] and Minutia Cylinder-Code (MCC) SDK [30] [31] [32] [33] before and after incorporating our proposed hierarchical registration algorithm as a pre-registration before the identification.

When reporting the rank identification accuracies, for Good quality, there are 88 match scores and 88 \( \times \) 257 non-match scores, for Bad and Ugly qualities, there are 85 match scores and 85 \( \times \) 257 non-match scores respectively. When we report the rank identification accuracy for the entire NIST-SD27 database (All category), then there are 258 match scores and 258 \( \times \) 257 non-match scores.

NIST-Bozorth3 is a minutiae based fingerprint matcher that is specially developed to deal with latent fingerprints. This matcher is part of the NIST Biometric Image Software (NBIS) [29].
developed by NIST. MCC-SDK is a well known minutiae matcher more adapted to good quality
fingerprints with reasonable number of minutiae in both query and reference templates. Both
NIST-Bozorth3 and MCC-SDK are publicly available. We show the performance accuracy of
the matcher using Cumulative Match Characteristic (CMC) curves.

7.1. Experiment 1: Choosing the best orientation field for tenprints

Fig. 3 shows the CMC curve of the NIST-Bozorth3 matcher when using MANUAL_OF
for latent against various other OF estimation techniques for tenprints while performing pre-
registration using our proposed hierarchical method. We can observe that the rank identification
accuracy has a consistent improvement when AVG_OF is used for tenprints.

Based on this result, we have chosen AVG_OF as the orientation field for tenprints in remain-
ing experiments reported here.

7.2. Experiment 2: Pre-Registration

In this experiment, we perform pre-registration using our registration algorithm to reduce
the minutiae search space of the tenprint minutiae set, and then use the reduced minutiae set
template as the reference template for the matcher. We used NIST-Bozorth3 and MCC-SDK as
the minutiae-based matchers.

For latents, MANUAL_OF and DICT_OF were used, and for the tenprints, we used AVG_OF
to report the rank identification accuracies in this experiment. We also analyze separately the
performance of the matcher using correlation only based registration and using hierarchical reg-
istration.
7.2.1. NIST-Bozorth3

Fig. 4 and Fig. 5 show the CMC curve of NIST-Bozorth3 for two different registration levels when MANUAL_OF and DICT_OF is used for latents respectively.

Fig. 4(a) shows the rank identification accuracy of NIST-Bozorth3 when correlation based registration (Level 1) of our algorithm is used as pre-registration, and also without using pre-registration (MANUAL_OF for latents). We see a significant and consistent improvement in the rank identification accuracy for all the quality categories when incorporating the proposed pre-registration.

Fig. 4(b) shows the rank identification accuracy of NIST-Bozorth3 when hierarchical registration (Level 2) of our algorithm is used as pre-registration with MANUAL_OF for latents. Here, we notice a consistent improvement in the CMC curve for all subjective quality categories compared to the correlation based registration. Especially there is a significant improvement for both Bad and Ugly quality categories.

Table 2: Rank-1 identification for NIST-Bozorth3 with correlation based pre-registration and hierarchical registration when MANUAL_OF is used for latents.

<table>
<thead>
<tr>
<th>Quality</th>
<th>Bozorth3 DIRECT(%)</th>
<th>Bozorth3 L1(%)</th>
<th>Bozorth3 L2(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>68.60</td>
<td>77.52</td>
<td>78.29</td>
</tr>
<tr>
<td>Good</td>
<td>77.27</td>
<td>85.23</td>
<td>86.36</td>
</tr>
<tr>
<td>Bad</td>
<td>60.00</td>
<td>70.59</td>
<td>72.94</td>
</tr>
<tr>
<td>Ugly</td>
<td>68.24</td>
<td>76.47</td>
<td>75.29</td>
</tr>
</tbody>
</table>

Table 2 summarizes the Rank-1 identification accuracy of NIST-Bozorth3 for both correlation based registration and hierarchical registration when MANUAL_OF is used for latents. The column DIRECT represents the Rank-1 identification accuracy of NIST-Bozorth3 when no pre-registration is applied to the minutiae set. Column L1 and L2 represent the Rank-1 identification
accuracy for correlation based registration (Level 1) and hierarchical based registration (Level 2) respectively.

Similarly, Fig. 5(a) and Fig. 5(b) shows the rank identification accuracy of NIST-Bozorth3 when correlation based pre-registration and hierarchical pre-registration were applied using DICT_OF for the latents. Table 3 summarizes the Rank-1 identification accuracy in this case. Similar results compared to using MANUAL_OF for the latents are also obtained here when considering DICT_OF. This proves the robustness of the DICT_OF method for obtaining a reliable OF even with very difficult latents and the feasibility of our method as a fully automatic tool.
Table 3: Rank-1 identification for NIST-Bozorth3 with correlation based pre-registration and hierarchical registration when `DICT_OF` is used for latents.

<table>
<thead>
<tr>
<th>Quality</th>
<th>DIRECT(L1)</th>
<th>DIRECT(L2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>68.60</td>
<td>75.19</td>
</tr>
<tr>
<td>Good</td>
<td>77.27</td>
<td>85.23</td>
</tr>
<tr>
<td>Bad</td>
<td>60.00</td>
<td>68.24</td>
</tr>
<tr>
<td>Ugly</td>
<td>68.24</td>
<td>71.76</td>
</tr>
</tbody>
</table>

7.2.2. **MCC-SDK**

Fig. 6 shows the CMC curve of MCC-SDK for the two registration levels considered when `MANUAL_OF` is used for latents. Fig. 6(a) and Fig. 6(b) show the rank identification accuracy of MCC-SDK when correlation based pre-registration and hierarchical pre-registration were applied respectively. Table 4 summarizes the Rank-1 identification accuracy in this case. The overall Rank-1 accuracy improved from 78.3% to 79.4% when incorporating Level 1 pre-registration, and to 79.4% when hierarchical based pre-registration (Level 2) is incorporated. Even though the improvement is small, it is consistent and increases for Bad and Ugly quality categories when we look beyond Rank-1.

<table>
<thead>
<tr>
<th>Quality</th>
<th>MCC-SDK Direct(L1)</th>
<th>MCC-SDK Direct(L2)</th>
<th>MCC-SDK Direct(L2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>78.29</td>
<td>79.46</td>
<td>79.46</td>
</tr>
<tr>
<td>Good</td>
<td>96.59</td>
<td>97.73</td>
<td>97.73</td>
</tr>
<tr>
<td>Bad</td>
<td>72.94</td>
<td>75.29</td>
<td>75.29</td>
</tr>
<tr>
<td>Ugly</td>
<td>64.71</td>
<td>64.71</td>
<td>64.71</td>
</tr>
</tbody>
</table>

Table 4: Rank-1 identification for MCC-SDK with correlation based pre-registration and hierarchical registration when `MANUAL_OF` is used for latents.

7.3. **Experiment 3: Parameters - Rotation step size, Radius**

In this experiment, we tried study the quantization step for rotation alignment (Step 3 in Algorithm) as well as the best radius of the circular region (Step 8 in Algorithm) to generate the subset of minutiae from the tenprint minutiae set. We used `MANUAL_OF` for the latents, `AVG_OF` for tenprints and performed hierarchical registration on NIST-Bozorth3 matcher.

From Fig. 7(a) we can observe that when we use a step size (X-axis) for the rotation equal to 1°, we obtain the best performance in terms of rank identification accuracy (Y-axis). We looked at the Rank-5 identified accuracy of the NIST-SD27 database (All category) to evaluate the performance, and looked at the step size varying from 1° to 25°. Also interestingly, the performance is not very much degraded with large steps, which can justify the use of large steps in some scenarios when computation speed is prioritized.

With 1° as the step size, we studied the effect of the radius of the circular region. We observe that the optimal radius is obtained by using a scale factor of 0.7 on the length of the diagonal for the bounding box. Fig. 7(b) shows the Rank-5 accuracy for various scales of the radius ranging from 0.6 to 1.4 scale factor in X-axis and the corresponding Rank-5 accuracy in Y-axis.
(a) Change in Rank-5 accuracies when increasing the step size in the range $1^\circ$ to $25^\circ$

(b) Change in Rank-5 accuracies when changing the scale factor from 0.6 to 1.4

Figure 7: Finding the optimal value for rotation step size and radius scales using NIST-Bozorth3 matcher.

<table>
<thead>
<tr>
<th>Quality</th>
<th>NIST-Bozorth3 DIRECT(%)</th>
<th>NIST-Bozorth3 with L2(%)</th>
<th>MCC-SDK DIRECT(%)</th>
<th>MCC-SDK with L2(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>68.60</td>
<td>78.29</td>
<td>78.29</td>
<td>80.62</td>
</tr>
<tr>
<td>Good</td>
<td>77.27</td>
<td>85.23</td>
<td>96.59</td>
<td>95.45</td>
</tr>
<tr>
<td>Bad</td>
<td>60.00</td>
<td>75.29</td>
<td>72.84</td>
<td>80.00</td>
</tr>
<tr>
<td>Ugly</td>
<td>68.24</td>
<td>74.12</td>
<td>64.71</td>
<td>65.88</td>
</tr>
</tbody>
</table>

Table 5: Rank-1 identification for NIST-Bozorth3 and MCC-SDK with optimal parameters.

7.4. Experiment 4: Best result obtained

With the optimal parameters estimated from our experiments, we have obtained the best performance boost for the matchers when using the hierarchical registration as a pre-registration. Fig. 8(a) and Fig. 8(b) shows the CMC curve for both NIST-Bozorth3 and MCC-SDK with the optimal parameters with the hierarchical pre-registration. MANUAL_OF was used for latents and AVG_OF was used for tenprints. Table 5 summarizes the Rank-1 identification accuracy of NIST-Bozorth3 and MCC-SDK for the optimal parameters (rotation step size with $1^\circ$ and radius scale factor of 0.7).

Using our registration algorithm as a pre-registration, we were able to boost the overall Rank-1 identification accuracy from 68.60% to 78.29% for NIST-Bozorth3, and from 78.29% to 80.62% for MCC-SDK. In other regions of the CMC curve the improvement is even higher.

8. Conclusions

We have proposed an orientation field based registration algorithm for partial fingerprints. When we use our hierarchical registration algorithm as a pre-registration stage and reduce the search space of minutiae in the tenprint minutiae set, we were able to significantly boost the performance of two popular minutiae matchers using challenging and realistic data. The main
objective of our research was to improve the rank identification accuracy for poor quality latents, and we were able to obtain consistent and significant improvement for both Bad and Ugly quality category of latents from NIST-SD27.

Upon studying various orientation field estimation techniques for fingerprints to be used in our registration, we have noticed that the best representative orientation field for tenprints was obtained by averaging a gradient based orientation field estimated from the fingerprint image and the orientation field reconstructed from the minutiae set. This gave the best performance. For latents, we studied two types of orientation fields corresponding to two different scenarios: with manual intervention and fully automated procedure. We obtained the best performance while using manually extracted orientation field for latents, and also a significant improvement with automated dictionary-based orientation field estimation.

We also observed that for a large quantization step in the rotation alignment, we have not degraded the performance very much, and while matching, we have reduced the size of the minutiae search space in the tenprint to good extent which accounts for overall efficiency of our proposed method. Also, we have established the feasibility of our method as a fully automatic tool.

References

[29] http://www.nist.gov/itl/iaid/ig/nbis.cfm (NBIS Release 4.2.0)