PARTIAL FINGERPRINT REGISTRATION FOR FORENSICS USING MINUTIAE-GENERATED ORIENTATION FIELDS

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ABSTRACT

Minutia based matching scheme is the most widely accepted method for both automated as well as manual (forensic) fingerprint matching. The scenario of comparing a partial fingerprint minutia set against a full fingerprint minutia set is a challenging problem. In this work, we propose a method to register the orientation field of the partial fingerprint minutia set to that of the orientation field of full fingerprint minutia set. As a consequence of registering the partial fingerprint orientation field, we obtain extra information that can augment a minutia based matcher by reducing the search space of minutiae in the full fingerprint. We present the accuracy of our registration algorithm on NIST-SD27 database, reporting separately for both subjective and quantitative quality classification of NIST-SD27. The registration performance accuracy is measured in terms of percentage of ground truth minutiae present in the reduced minutiae search space generated by our algorithm.

***Index Terms*—** Partial fingerprints, registration, orientation field reconstruction, Schwarz inequality, Hilbert space, second-order tensors.

1. INTRODUCTION

The most widely adapted representation scheme used by many fingerprint matching systems is the minutia-based representation scheme. This minutia-based representation is also important because of its strict analogy with the forensic friction ridge analysis performed by forensic examiners [1]. The minutia-based decision is accepted as a proof of identity legally by courts in almost all countries around the world [2].

Most machine algorithms for minutia-based matching assume that the size of the minutia set is approximately the same between the query and reference minutia set for improved matching accuracy [3]. There can be several situations where a partial fingerprint minutia set is to be compared against a full fingerprint minutia set.

Partial fingerprints can arise in a number of situations, for example [3] [4]:

- the unintentional traces of the fingerprint left by the perpetrator in a crime scene (*latent* fingerprints are mostly partial in nature).
- due to small size of the fingerprint capturing/acquisition devices (compact silicon-chip based sensors).
- an already enrolled/acquired fingerprint has noisy regions and are left with only a partial good/recognizable region for identification.

The performance of the existing partial fingerprint identification systems/algorithms mainly depends on the image quality, the number of minutia available, and other derived and extended features that can be obtained from the partial fingerprint region. Various approaches in partial fingerprint identification [4] include the use of localized secondary features derived from relative minutia information [3], using representative points along ridge lines in addition to minutiae [5], and use of Level-3 features such as dots and incipient ridge units as extended features [6].

For any partial fingerprint identification system, it will be advantageous if we can reduce the minutiae search space of the full fingerprint minutia set with respect to the partial fingerprint minutia set during comparison. One such strategy to reduce the minutiae search space is to register the orientation field (OF) of the partial fingerprint with that of the OF of full fingerprint. We then need to perform minutia comparison only with those minutiae that fall in the subregion of the full fingerprint where the partial fingerprint is registered. Such a registration methodology can yield extra information that can augment minutia-based matching strategies.

In this work, we propose a registration algorithm using the OF of both partial and full fingerprint solely generated from their respective minutia sets as proposed in [7]. The work by Feng and Jain [7] in reconstructing the fingerprint image from minutia sets alone, and successfully launching attacks against fingerprint recognition system indicates that the

978-1-4799-4370-8/14/$31.00 ©2014 IEEE

fidelity of the reconstructed OF to the actual OF is significant. Also, the performance of the algorithm in reconstructing the OF did not drop much even when only 60% of minutiae are only available for OF reconstruction.

The ability to reconstruct the OF with only few minutiae supports the rationale behind using this OF reconstruction technique to perform the partial fingerprint registration against a full fingerprint. In the following sections, we discuss the database used in the experiments, the similarity measure crucial in the registration, a detailed description of the partial fingerprint registration algorithm, followed by experiments, results and discussion.

2. DATABASE

The NIST Special Database 27 (NIST-SD27) [8] is a publicly available forensic fingerprint database which provides minutia sets for latent and its matching tenprint images. The NIST-SD27 minutia set database is broadly classified into two [8] [9]: 1) *ideal*, and 2) *matched* minutia set database. The *ideal* minutia set for latents was manually extracted by a forensic examiner without any prior knowledge of its corresponding tenprint image. The *ideal* minutiae for tenprints was initially extracted using an Automated Fingerprint Identification System (AFIS), and then these minutiae were manually validated by at least two forensic examiners. The *matched* minutia 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 minutia set) was established manually by a forensic examiner looking at the images and the *ideal* minutiae.

The NIST-SD27 database consists of 258 latent fingerprint images and 258 mated tenprint images. The latent fingerprint images are of varying qualities. It already contains a classification of the latent fingerprints based on the subjective quality of the image into Good, Bad and Ugly, containing 85, 88 and 85 images respectively determined by the forensic examiner. In [10], it is shown that there is a correlation between these subjective classification and matching performance.

Jain and Feng in [10] also introduced another three quality measures for categorizing the NIST-SD27 database based on the total number of minutiae (n) present in the latent minutia set: Large ($n > 21$), Medium ($13 < n < 22$) and Small ($n <= 13$) and contains 83, 82 and 93 images respectively. We used these subjective and quantitative categorizations to report the performance of our algorithm.

3. SIMILARITY MEASURE

The space of discrete images of same size taking scalar values is a vector space [11, Chapter 3]. A vector space which has a scalar product defined in itself is called a Hilbert space. Let $\mathbf{U}$ and $\mathbf{V}$ be discrete images of 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:

$$\frac{|\langle \mathbf{U}, \mathbf{V} \rangle|}{\|\mathbf{U}\| \times \|\mathbf{V}\|} \leq 1 \tag{1}$$

holds for $\mathbf{U}$ and $\mathbf{V}$. Here, $\langle \mathbf{U}, \mathbf{V} \rangle$ is the scalar product between $\mathbf{U}$ and $\mathbf{V}$ calculated as :

$$\langle \mathbf{U}, \mathbf{V} \rangle = \sum_{r,c} \mathbf{U}(r,c)^* \cdot \mathbf{V}(r,c) \tag{2}$$

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

The L_2 norm $\|\mathbf{U}\|$ is calculated as:

$$\|\mathbf{U}\| = \left[\sum_{r,c} \mathbf{U}(r,c)^* \cdot \mathbf{U}(r,c) \right]^{1/2} \tag{3}$$

and similarly for $\|\mathbf{V}\|$.

The normalized correlation between $\mathbf{U}$ and $\mathbf{V}$, referred to as Schwarz Similarity (SS) hereafter is defined as:

$$SS(\mathbf{U}, \mathbf{V}) = \frac{|\langle \mathbf{U}, \mathbf{V} \rangle|}{\|\mathbf{U}\| \times \|\mathbf{V}\|} \tag{4}$$

Because of Eq.(1), the interval for SS 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 $SS(\mathbf{U}, \mathbf{V})$ is 1, then both $\mathbf{U}$ and $\mathbf{V}$ are viewed as most similar patterns, and when $SS(\mathbf{U}, \mathbf{V})$ is 0, they are least similar [11].

4. ALGORITHM

We present the algorithm of partial fingerprint registration using the forensic terminologies for the fingerprint. The partial fingerprint is mentioned as latent, and the full fingerprint is mentioned as tenprint. The algorithm to register the orientation field of the latent fingerprint minutia set with that of the tenprint is detailed as follows:

Step 1: Given a latent minutia set L and a tenprint minutia set T, reconstruct the orientation field from the minutia using the algorithm defined in [7]. This orientation field is in the range $[-90, +90]$ degrees, and can be obtained for 8×8 or 16×16 block size. In our experiments, we used 16×16 block size for the orientation field (see Figs. 1(a), 1(b)). The target of the registration algorithm is to locate the region depicted in Fig. 1(c).

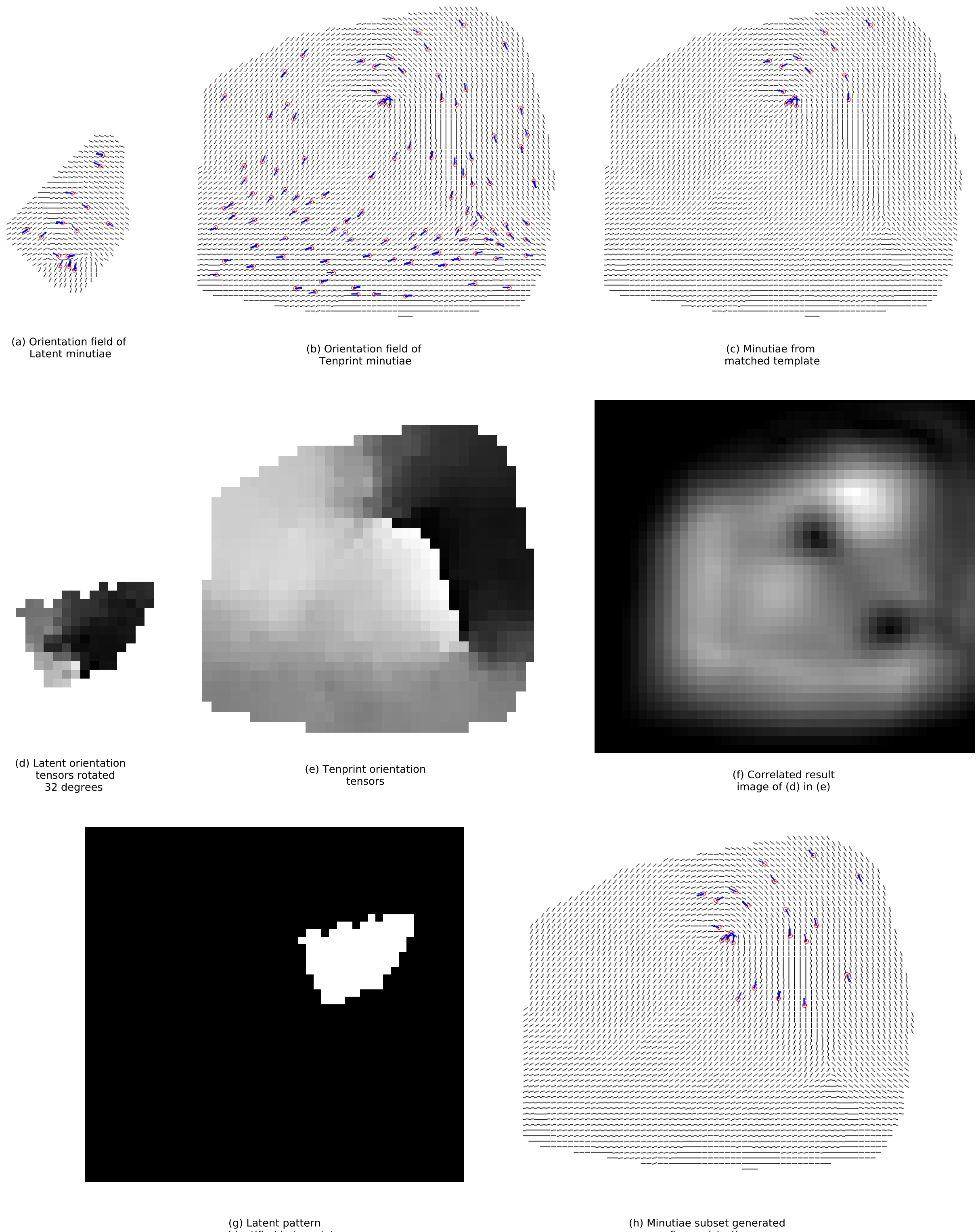

Fig. 1. Various stages in the registration algorithm shown on B101L9 (latent) and B101T9 (tenprint) of NIST-SD27. (a) and (b) are the orientation field (OF) generated from the ideal minutia set, with the minutiae plotted over the OF. (c) is the region in the tenprint that is to be found after registration of (a) into (b), (d) and (e) are the orientation tensors of latent and tenprint. Here (d) is rotated $+32^{\circ}$. (f) is the result of correlating (d) and (e). (g) is the region were latent pattern is identified in tenprint. (h) is the minutia region selected by our registration algorithm in this example.

Step 2: Generate the orientation tensors for the latent L and tenprint T in double angle (i.e, in the range $[-180, +180]$ degrees) using complex numbers, as follows:

$$\begin{aligned}\bar{L} &= \exp(i \times 2 \times \theta_L) \\ \bar{T} &= \exp(i \times 2 \times \theta_T)\end{aligned} \tag{5}$$

where i is the complex number $\sqrt{-1}$, θ_L and θ_T are the angles of L and T from Step 1.

The complex field, which depicts the local orientation thus obtained can be viewed as a field of second-order tensors, which in turn is a Hilbert Space. We can find the scalar product between $\bar{L}$ and $\bar{T}_s$, as follows:

$$\langle \bar{L}, \bar{T}_s \rangle = \sum_{r,c} \bar{L}(r, c)^* \cdot \bar{T}_s(r, c) \tag{6}$$

where r, c are the indices, $\bar{L}(r, c)^*$ is the complex conjugate of $\bar{L}(r, c)$ and $\bar{T}_s$ is a subregion of $\bar{T}$ that is of same size as $\bar{L}$ located at a position indexed by s.

Step 3: Define the bounding box for the latent orientation tensors $\bar{L}$ by discarding the background. The bounding box can be estimated by the minimum and maximum row and column numbers that correspond to the foreground of latent orientation tensors, see Fig. 1(d). The orientation field for the tenprint image is shown in Figure 1(e). This $\bar{L}$ in Fig. 1(d) is the pattern that we want to locate in the tenprint $\bar{T}$ in Fig 1(e).

Step 4: When searching for the pattern $\bar{L}$ in $\bar{T}$, it is possible that $\bar{L}$ is not perfectly aligned with $\bar{T}$, rotation wise. To compensate for the rotation alignment, we need to test the latent $\bar{L}$ against tenprint $\bar{T}$ for various rotations of $\bar{L}$. In our experiments, we rotate $\bar{L}$ in the range $[-45, +45]$ degrees with a step size $\Delta\theta$ of 1 degree. We denote the rotated $\bar{L}$ as $\bar{L^\theta}$. A geometric rotation of the field implies an appropriate rotation of tensor field (complex values) with $2\Delta\theta$.

Step 5: Correlate the conjugate of the latent orientation tensor $\bar{L^\theta}^*$ with $\bar{T}$ to generate all possible $\langle \bar{L^\theta}, \bar{T}_s \rangle$, the scalar products between $\bar{L^\theta}^*$ and $\bar{T}_s$ for varying locations s. The result of this operation can be seen as a complex image indexed by s which is of the size of $\bar{T}$, see Fig. 1(f).

Step 6: From the correlated result, find the point (or index) $s = (r_m^\theta, c_m^\theta)$ where the magnitude of the scalar product is maximum, and $s = (r_p^\theta, c_p^\theta)$ where the phase is minimum. Both maximum magnitude and minimum phase convey the region in $\bar{T}$ where $\bar{L^\theta}$ agrees the most.

Step 7: Find the similarity based on Schwarz inequality as explained in Section 3, between $\bar{L^\theta}$ and $\bar{T_s^m}$ centered at (r_m^θ, c_m^θ) and $\bar{T_s^p}$ centered at (r_p^θ, c_p^θ). The L_2 norms $\|\bar{L^\theta}\|$, $\|\bar{T_s^m}\|$ and $\|\bar{T_s^p}\|$ for different θ are equal because the orientation tensors $e^{i2\theta_L}$ and $e^{i2\theta_T}$ are not estimated from the gray pixel gradients, but reconstructed from minutia orientations. Consequently, these orientation tensors are complex numbers falling on a unit circle, representing the local direction. So, the magnitude of the orientation tensors thus obtained are always 1.

Step 8: The θ for which SS is maximum is deemed to be the best alignment between latent and tenprint, and (r^θ, c^θ) is the point in tenprint where the latent is registered. This (r^θ, c^θ) corresponds to either of (r_m^θ, c_m^θ) or (r_p^θ, c_p^θ) for which SS is maximum.

Step 9: The point (r^θ, c^θ) estimated as

$$\max_{\theta, s=(r^\theta, c^\theta)} [SS(\bar{L^\theta}, \bar{T_s^m}), SS(\bar{L^\theta}, \bar{T_s^p})] \tag{7}$$

is the center of the latent orientation tensor pattern that we have identified in the tenprint, see Fig. 1(g).

Step 10: With (r^θ, c^θ) as center, and radius as half the diagonal length of the bounding box of latent orientation tensors, we generate a subset of minutiae from the tenprint minutia set which falls inside this circular region, see Fig. 1(h).

5. EXPERIMENTS

We used the NIST-SD27 database detailed in Section 2 for the experiments. To register the OF of latent against OF of tenprint images, we used the ideal minutiae dataset from NIST-SD27. The performance of the proposed registration algorithm is measured looking at the percent of the ideal minutiae that we detected in the registered region that is present in the corresponding matched minutia set. We only used the matched dataset (ground truth established by forensic examiner) to check this overlap. The matched minutia sets are a subset of ideal minutia set, but the location and orientation information are not exactly the same. There are slight variations in the location and orientation attributes between ideal and its corresponding matched minutia set originated in the annotations by the experts.

For example, G028T1I and G028T1M of NIST-SD27 contain 123 and 20 minutiae respectively. G028T1I is the ideal minutia set and G028T1M is its corresponding matched minutia set. The pair $(X, Y, Orientation) = (562, 189, -68)$ of ideal and $(564, 182, -73)$ of matched are supposed to be same minutia in the fingerprint. However there is a slight variation with an euclidean distance of 7.2 pixel units. This variation might be because of the uncertainty introduced by the software used by the examiner while generating the matched minutia set. In general, there is a small non-linear deformation between the ideal and matched minutia sets of the tenprints, and we fixed a threshold of 12 pixel units to compensate for this. If the distance between a minutia from

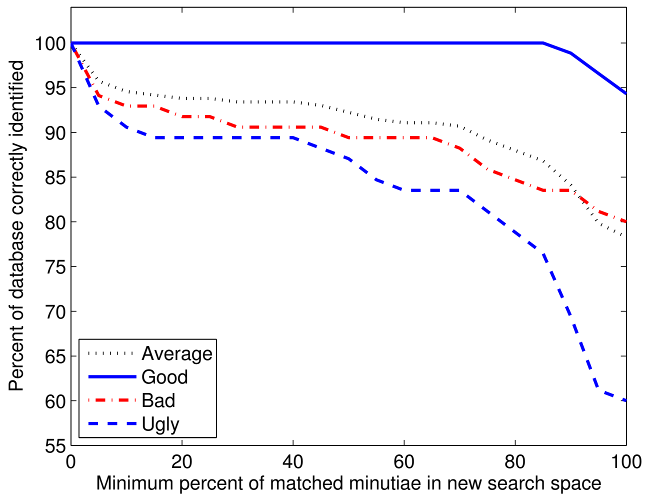

Fig. 2. Results for subjective quality classification.

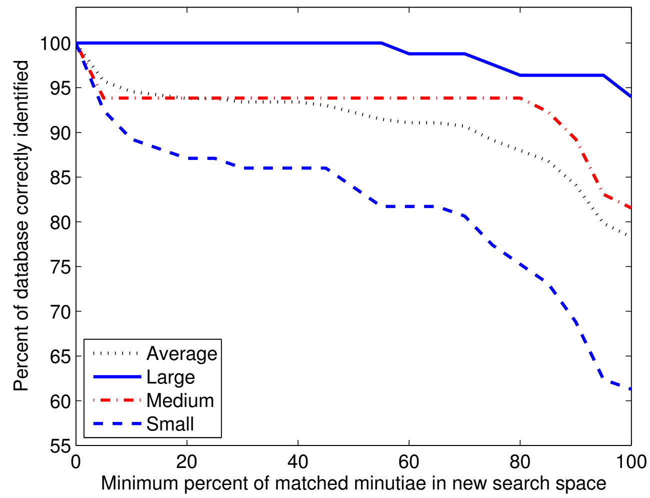

Fig. 3. Results for different number of minutiae in the latents.

ideal and matched sets is less than 12 pixel units, then they are assumed to be corresponding mated pairs. A detailed study on NIST-SD27 where these kind of discrepancies between the ideal and matched minutia sets is reported in [12], where a refined version of the ground truth minutia sets for NIST-SD27 is made publicly available [12].

Together with the overall performance on the NIST-SD27 database, we report experiments on both the subjective quality classification {Good, Bad, Ugly} as well as on the number of minutia {Large, Medium, Small} as detailed in Section 2.

5.1. Performance measurement protocol

The registration algorithm finds a subregion in the tenprint that best aligns the latent and tenprint orientation fields. Based on this registration, a subset of minutiae from tenprint minutiae set is chosen as described in Step 10 of Section 4. The ground truth (otherwise called *matched*) minutia set in NIST-SD27 can be used to check how many of the actual mated minutiae are present in this minutiae subset. In our experiments, we have only performed the match (genuine/client) comparisons to study the initial performance of our algorithm. The non-match (impostor) comparisons can be studied only by employing a minutia based matcher to see how the identification performance varies. We used only ground truths to evaluate the match comparisons of our algorithm. If the distance between a minutia from the matched set and the minutia in the search space suggested by our algorithm is less than 12 pixel units, then we conclude that a mated pair has been identified by our algorithm.

5.2. Results

Together with the performance of our registration algorithm for the entire database , we also report the performance of our algorithm on the different subsets defined in Section 2.

Fig. 2 shows the performance of our registration algorithm for the entire database as well as for the subjective quality classification of the database, and Fig. 3 for the classification based on the number of minutiae in latents. The X-axis is the minimum percent of matched minutiae that should be contained in the reduced minutia search space defined by our algorithm and Y-axis is the percentage of database that satisfies the threshold. For example, 89% of the entire database in the average scenario (without quality classification) contains at least 75% of the matched minutiae in the new search space generated by our registration algorithm.

Threshold	Average	Good	Bad	Ugly	Large	Medium	Small
75	89	100	85	82	97	94	78
80	88	100	85	79	97	94	76
85	87	100	84	77	97	93	74
90	85	99	84	70	97	90	69
95	80	97	82	62	97	84	63
100	79	95	80	60	94	82	62

Table 1. Performance of the registration algorithm for selected thresholds. All values are in percentage(%).

Table 1 summarizes the performance of our registration algorithm for selected thresholds. The first column in the table (Threshold) denotes the minimum percent of matched minutiae that should be present in the new search space generated by our algorithm and the remaining columns show how much of the database was completely identified under the given threshold for various categories of the database. Average classification denotes the whole database without any classification.

6. DISCUSSION

Experimental results show that our algorithm can register the partial fingerprint orientation field with that of its corresponding tenprint and estimate a subset of the tenprint minutia set with good accuracy. If we search whether 100% of the matched minutia is present in the minutia subspace estimated by our algorithm, then we are able to identify in average (the entire database) with 79% accuracy, and with 95% and 94% for Good and Large classification, 80% and 82% for Bad and Medium classification, and 60% and 62% for Ugly and Small classification respectively. At 85% threshold, still we are able to identify the database with good accuracy, with 100% identification rate for Good classification.

This shows that, using our registration algorithm, we can obtain extra information that can augment any minutia based matcher by reducing the search space for the matcher, and correctly locating the subregion in tenprint that corresponds to the partial latent fingerprint in case of Good quality latents. The deteriorated performance in case of Bad and Ugly classification can be concluded mainly because of the few number of minutia and the degraded quality of the estimated orientation field. This conclusion is also supported by the results obtained by Medium and Small classification. A detailed analysis on how this registration algorithm can be incorporated to improve the identification of minutia-based matchers is in order.

Acknowledgment

R.K. is supported by Marie Curie Fellowships under project BBfor2 (FP7-ITN-238803). This work has also been partially supported by Spanish Guardia Civil, Cátedra UAM-Telefónica, and projects Bio-Shield (TEC2012-34881) and Contexts (S2009/TIC-1485).

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