Estimation of cylinder quality measures from quality maps for Minutia-Cylinder Code based latent fingerprint matching

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Abstract

Poor quality of fingerprint data is one of the major problems concerning latent fingerprint matching in forensic applications. Local quality of fingerprint plays a very important role in this application field to ensure high recognition performance. Although big progress has been made in matching of fingerprints using local minutiae descriptors, in particular Minutia Cylinder-Code (MCC), automatic latent fingerprint matching continues to be a challenge. Previously we proposed a matching algorithm that uses minutiae information encoded by MCC with integrated local quality measures associated to each MCC called cylinder quality measures. In our previous work, cylinder quality measures for latent case have been proposed by combining the subjective qualities of individual minutiae involved. In this paper, we propose an alternative method to estimate the cylinder quality measures directly from fingerprint quality maps, in particular ridge clarity maps, by taking into account the number of involving minutiae as well. Integration of MCC with the proposed cylinder quality measures was evaluated through experiments on the latent fingerprint database NIST SD27. These experiments show clear improvements in the identification performance of latent fingerprints of ugly quality.

1. Introduction

Fingerprint is one of the most widely used biometric traits for personal identification. For over one hundred years, it has been accepted as an important source of evidence for forensic human identification in the law enforcement agencies worldwide [1].

There exist three main types of fingerprint in forensics applications: 1) rolled, which is collected by rolling a finger from nail to nail on the capturing surface; 2) plain, which is collected by pressing a finger down on the capturing surface; 3) latent, which is collected from surfaces at crime scenes. Rolled and plain fingerprints have usually large amount of ridge details, which are normally believed to be sufficient information for identification. Latent fingerprints have usually the least amount of details and information available for identification.

In latent fingerprint identification, a latent fingerprint is usually compared with the rolled/plain fingerprints already registered in a database. Despite the fact that the recognition performance of Automated Fingerprint Identification Systems (AFISs) has been improved a lot for rolled/plain fingerprints, human intervention is still necessary for latent fingerprint identification, especially in feature extraction. Therefore one of the main challenges is a large number of cases, in particular high-profile cases, where forensic experts are usually under time pressure when identifying fingerprints. Therefore, it is very important that the fingerprints sent to a final visual comparison be carefully selected so that forensic expert can spend an adequate amount of time for their final examination. One way to achieve this goal is to design an efficient automatic latent to rolled fingerprint matching system that is able to provide a quantitative estimate of the similarity between the latent and rolled prints taking into account a quality of latent fingerprint. In this case, a "Semi-Lights-Out System" [2] can be developed, where some human intervention is allowed during minutiae extraction from a latent fingerprint. The system then outputs a short list of candidates by ranking that need to be examined by the forensic expert to determine fingerprints of the highest visual similarity.

Highly discriminative minutiae-based matching is the most widely adopted approach in forensic fingerprint identification [3, 4]. However latent fingerprint matching is extremely challenging mainly due to: 1) poor quality of latent prints for which the clarity of ridge impressions is low, 2) small finger area in latent prints to be compared to rolled prints of big finger area, 3) large nonlinear distortion because of pressure variations [2].

The local minutia matching techniques have been proposed in order to address some weaknesses of global minutiae matching [3] like non-robustness to nonlinear distortions, need for accurate global alignments, and high computational effort. These techniques are based on local minutiae structures which are descriptors encoding the relationships between each minutia and its neighboring minutiae in terms of some measures invariant to rotation and translation. The local minutiae structures define a region around each minutia by considering, e.g., all minutiae closer than a given radius (fixed-radius based techniques). In particular, Minutiae Cylinder-Code (MCC) representation, recently proposed in [5], obtained remarkable performance with respect to state-of-the-art local minutiae descriptors [6, 7]. One way to improve the accuracy of latent fingerprint identification is to combine modern local minutia matching techniques with subjective or objective local quality measures [8, 9].

Latent fingerprint quality has a significant impact on matching accuracy of fingerprint identification systems [2]. Local quality measures, assigned to the blocks within the image, are mainly combined into a global quality measure for the whole fingerprint image [10, 11]. The local quality measures can be also employed directly in the local matching, for example, to weight the local scores for their contribution to the global matching score. Incorporating local quality measures in minutiae-based matching has been an interesting problem studied in this context [12, 13, 14, 9]. In our previous work [15], we proposed that cylinder quality measures for latent fingerprints can be computed by combining the subjective qualities of the involving minutiae. Recently Yoon et el. in [11] proposed an approach to generate ridge clarity maps for latent fingerprints. Based on their empirical results, they concluded that the (average) ridge clarity together with the number of minutiae are the two significant features representing the latent fingerprints. In this paper, we propose a new method to estimate the cylinder quality measures directly from fingerprint quality maps, in particular the ridge clarity maps proposed in [11]. We have also taken into account the number of contributing minutiae to the newly proposed measure, which is showed to be an important quality factor.

The rest of this paper is organized as follows. Section 2 provides a brief introduction to fingerprint quality maps and ridge clarity maps for latent fingerprints. Minutiae Cylinder Code (MCC) and its integration with the cylinder quality measures are introduced in Section 3. Then in Section 4, we propose new methods for obtaining cylinder quality measures from fingerprint quality maps. The experiments and results are presented in Section 5. Finally, conclusions are drawn in Section 6.

2. Fingerprint quality maps

Fingerprint quality estimation methods are generally categorized into three different groups [16]: 1) those based on local features; 2) those based on global features; 3) those based on a classification approach. The main focus of this paper is on the local approaches, which rely on local features of the fingerprint image. In such methods, the image is usually divided into nonoverlapping square blocks and the quality features are extracted from each block, resulting in a quality map where a local measure of quality is assigned to each block. This measure usually represents the clarity of the ridges and valleys, which can also estimate the extractability of the fingerprint features such as minutiae. Local orientation, Gabor filters, pixel intensity statistics, power spectrum and their combination have been the main local features already used for local quality assessment of the fingerprint images [16].

2.1. Ridge clarity maps

Although a variety of methods have been introduced for measuring the local quality of rolled/plain fingerprints, it is rather challenging to objectively assess the local quality of latent fingerprints due to missing ridge structures, mixture of ridge patterns, severe background noise, etc [11]. Recently in [11], Yoon et al. proposed an average ridge clarity measure for latent fingerprints, which is computed from a ridge clarity map containing the local clarity estimates in 16×16 pixel blocks within the latent fingerprint image. The ridge clarity in each block is estimated based on the 2-dimensional sine wave representations of the ridges in the form of $\omega(x, y) = a * \sin(2\pi f(x\cos\theta + y\sin\theta) + \phi)$ [17]. The procedure to obtain the ridge clarity map briefly consists of the four following steps:

1. Contrast enhancement of the original fingerprint image.
2. Estimating the parameters of the 2-D sine wave representations (a, f, θ, ϕ) for each block corresponding to the top two local amplitude maxima of its Fourier spectrum within the frequency range of $\left[\frac{1}{16}, \frac{1}{5}\right]$[1].
3. Obtaining a ridge continuity map by evaluating continuity conditions of the 2-D sine waves in adjacent blocks.
4. Computing the ridge clarity map via multiplying the ridge continuity of each block by the highest amplitude of its 2-D sine waves.

[1] The frequency range is selected based on the fact that the dominant ridge frequencies in a fingerprint image are generally in this range.

In Figure 1, the ridge clarity maps are shown for a latent fingerprint and a rolled tenprint from NIST SD27.

3. MCC based latent fingerprint matching

3.1. MCC

Local minutiae descriptors became very popular in modern fingerprint matching techniques. Among recently proposed local minutiae descriptors, Minutia Cylinder-Code (MCC) [5] has shown a relatively high performance for local matching [6]. MCC is a fixed-length minutiae descriptor which encodes the relationships between a central minutia and its neighboring minutiae within a fixed-radius circular area. It is to some extent invariant to rotation and translation, robust to skin distortions, and can be computed rather fast.

Given a set of minutiae (a minutiae template), the distance of one minutia to all its neighboring minutiae is considered as basis for creating the MCC. In addition to distance, the angular difference is taken into account using an additional dimension. Finally for each minutia a discretized 3D cylinder-shaped structure is created as MCC descriptor, whose base and height are related to the spatial and directional information, respectively.

3.2. Cylinder quality measures for MCC based matching

In this section, we describe our proposed method to incorporate the cylinder quality measures into MCC based matching process. The MCC based matching normally begins with computing all local similarities for every possible pair of cylinders from the two templates to be compared. Then these local similarities are combined into an overall similarity score between two minutiae templates (e.g., one corresponding to the latent and the other one corresponding to the rolled fingerprint). In [5, 7] several methods have been introduced to obtain a global score from the local similarities, almost all of them involve a careful selection of candidates among all possible pairs and then averaging over their (relaxed) similarities. The cylinder quality measures can be employed here in several ways: they can be used for example to reject the very low-quality cylinders from the list of potential candidates, or they can be applied as weights to the local similarities for candidate selection or final averaging. One approach can be to weight the local similarity between two cylinders based on their pairwise quality. Therefore, if the quality is high for cylinders in a pair, this pair gains more chance to be selected as a candidate and will contribute more to the global score than a pair of low quality cylinders. However this simple weighting strategy might not be so helpful mainly because the incompatible pairs that initially obtained a high similarity by chance might obtain even higher contribution if they are of high quality as well. What we propose here, to reduce the effects of this deficiency, is to utilize the cylinder qualities after a preselection phase through a relaxation approach like in [18, 5].

More precisely, given two templates of MCC descriptors, say $L = \{l_1, l_2, ..., l_{n_L}\}$ corresponding to a latent fingerprint and $T = \{t_1, t_2, ..., t_{n_T}\}$ corresponding to a rolled tenprint, the global matching $Score$ between the two templates is computed through the following steps[2]:

1. The local similarities between all possible pairs of descriptors respectively from the two templates ($n_L \times n_T$ pairs in total) are computed as in [5].

[2] All MCC related parameters used in the formulations, have been named same as in [5], except otherwise stated.

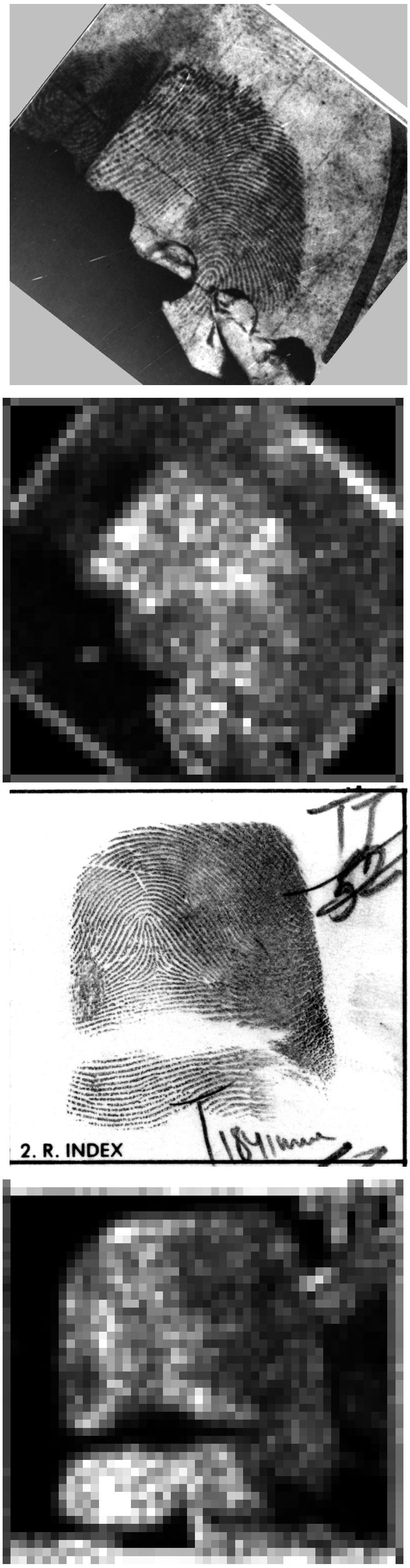

Figure 1: Ridge clarity maps for latent and rolled fingerprints

2. The n_R pairs having normally the top local similarities are pre-selected, e.g., using a Local Greedy Similarity (LGS) algorithm [7]. Note that n_R is usually greater than the number of final pairs (n_P) that contribute to the global score. Let P be the set of all selected pairs:

$$P = \left\{ \left(l_{r_j}, t_{c_j} \right) \right\},\ j = 1, ..., n_R,$$
$$1 \le r_j \le n_L,\ 1 \le c_j \le n_T,\ n_R = \min \left\{ n_L, n_T \right\}.$$

3. Through the relaxation phase, the local similarity of each pair is iteratively being modified based on its global relationship with the other pairs as follows: assuming $\lambda_j^{(0)}$ to be the initial similarity of pair j (i.e., $\left(l_{r_j}, t_{c_j} \right)$), the modified local similarity at iteration i of the relaxation procedure is:

$$\lambda_j^{(i)} = \omega_R \cdot \lambda_j^{(i-1)} + \left(\frac{1 - \omega_R}{n_R - 1} \right) \cdot \sum_{\substack{k=1 \\ k \ne j}}^{n_R} \left(\rho(j,k) \cdot \lambda_k^{(i-1)} \right), \tag{1}$$

where ω_R is a weighting parameter and $\rho(j,k)$ is the measure of compatibility between two pairs: $\left(l_{r_j}, l_{r_k} \right)$ and $\left(t_{c_j}, t_{c_k} \right)$, and can be computed as explained in [5] considering also its distortion-tolerant version in [7]. After executing n_{rel} iterations on all n_R pairs existing in P, the quality-based efficiency of pair j is calculated as:

$$qe_j = \frac{\lambda_j^{(n_{rel})}}{\lambda_j^{(0)}} \cdot Q_j, \tag{2}$$

where Q_j is a pairwise quality measure for pair j, and thus depends on both $Q_{l_{r_j}}$ and $Q_{t_{c_j}}$, that are quality measures corresponding to the MCC descriptors l_{r_j} and t_{c_j} respectively.

4. The n_P pairs with the highest quality-based efficiency qe_j are selected, and the final score is computed using a weighted average with pairwise qualities Q_j as weights:

$$Score = \frac{\sum_{j=1}^{n_P} \left(Q_j \cdot \lambda_j^{(n_{rel})} \right)}{\sum_{j=1}^{n_P} Q_j}. \tag{3}$$

With the definition given for quality-based efficiency, the final pairs are selected taking into account both factors of quality and compatibility with other pairs. It can also address the previously discussed problem of the pairs that obtained randomly an initial high similarity, by penalizing them in the relaxation process.

4. Cylinder quality measures from fingerprint quality maps

In our previous work [15], it was proposed that cylinder quality measures for latent fingerprints can be computed by combining the subjective qualities of the involving minutiae. In this section, we propose a new method to estimate the cylinder quality measures directly from fingerprint quality maps, in particular the ridge clarity maps described in Section 2.1. In the proposed measure, we also take into account the number of contributing minutiae to each cylinder. This is inspired by the empirical results in [11], based on which Yoon et el. concluded that the number of minutiae and the (average) ridge clarity are the

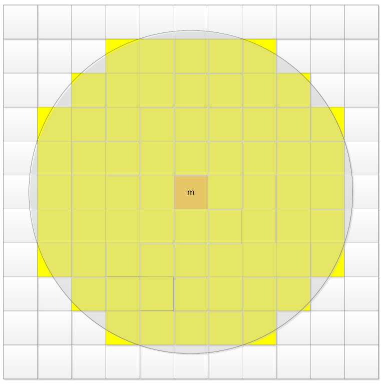

Figure 2: An example showing the 16×16 pixel blocks considered for computing the average ridge clarity within a cylinder of radius 75 pixels.

two significant features representing the quality of latent fingerprints. Our method is generally based on averaging the entries of the quality map within the area of a given cylinder. More specifically, given a cylinder C_m with the radius R pixels centered at minutia m, the cylinder quality measure, Q_{C_m}, is defined as:

$$Q_{C_m} = N_{C_m} \cdot \widetilde{Q}_{C_m}, \tag{4}$$

where N_{C_m} is the number of minutiae contributing to the cylinder and $\widetilde{Q}_{C_m}$ is an average quality contribution estimated from the fingerprint quality map.

Considering $\mathbf{QM}\,[xb, yb]$ to be quality of the block residing in the row xb and the column yb of the quality map, we propose two approaches for estimating $\widetilde{Q}_{C_m}$. In the first approach, $\widetilde{Q}_{C_m}$ is estimated based on the average quality in the blocks containing the minutiae involved in the cylinder, as follows:

$$\widetilde{Q}_{C_m} = \frac{1}{N_{C_m}} \sum_{i=1}^{N_{C_m}} \mathbf{QM}\,[xb_i, yb_i]\,, \tag{5}$$

where $[xb_i, yb_i]$ is the block containing the i-th minutia contributing to the cylinder C_m.

For example, if we consider 16×16 pixel blocks for the quality map, and a cylinder with radius 75 pixels fully inside the convex hull of all minutiae, the final blocks are those conatining minutiae among the 69 blocks around the central block (including itself) as depicted in Figure 2.

With the cylinder quality measures defined in Eq. (4), we have taken into account both the average ridge clarity and the number of minutiae within the cylinder area.

5. Experiments and results

5.1. Database

For our evaluations, we have considered the only publicly available database of latent fingerprints, NIST SD27 [19], which contains 258 latent fingerprint cases and their corresponding rolled tenprints. The cases are divided into three general categories: Good (88 cases), Bad (85 cases), and Ugly (85 cases) based on the overall quality of latent fingerprint images evaluated by examiners. The minutiae information (position and direction) is provided for all fingerprints in the database. The tenprints minutiae are extracted by an automatic AFIS system and the latent minutiae are marked manually by the professional latent examiners.

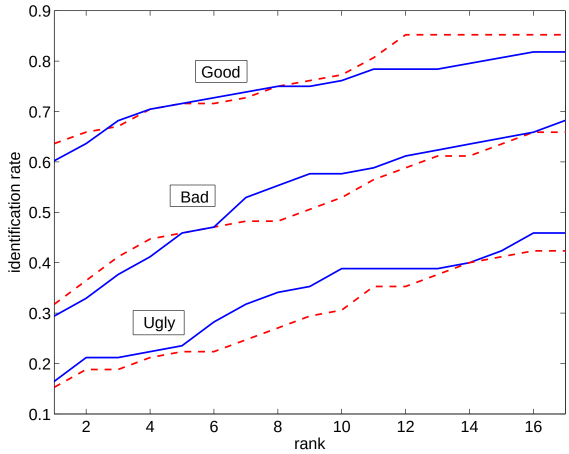

Figure 3: CMC curves showing the identification performance on Good, Bad and Ugly parts of NIST SD27 in presence (blue solid curves) and absence (red dashed curves) of cylinder quality measures.

5.2. Evaluations

The bit-based MCC descriptors (MCC16b) were firstly created using the parameters given in [7]. We also implemented the MCC based matching algorithm as proposed in [7], which involves a distortion-tolerant relaxation part. For our comparative evaluations, we consider two different scenarios with and without incorporating cylinder quality measures in the matching. The case without quality is equivalent to consider equal qualities for all cylinders. To incorporate cylinder quality, we firstly generate ridge clarity maps for all latent and rolled fingerprint images as explained in Section 2.1. Then for each MCC descriptor, a cylinder quality measure is computed according to Eqs (4) and (5) given in Section 4. The cylinder quality measures are used to obtain the pairwise quality (Q_j) needed for matching (see Eqs (2) and (3)). Here we also consider a common form of $Q_j = \sqrt{Q_{l_{r_j}} \times Q_{t_{c_j}}}$ as pairwise quality of the latent-rolled cylinder pair j. This means that the cylinder qualities of both latent and rolled cases have been taken into account in our experiments.

The Cumulative Match Characteristic (CMC) curves (identification rate vs. rank) are shown in Figure 3 separately for Good, Bad, and Ugly images within the NIST SD27 database both in presence and absence of cylinder quality measures. Incorporating the proposed cylinder quality measures shows an improvement in the identification performance for the Ugly category and also for the Bad category above some given rank. For example, the rank-10 identification rate is increased from 30.59% to 38.82% for the Ugly category and from 52.94% to 57.65% for the Bad category. On the other hand, there are some failures specially for the Good category which has also the highest average number of minutiae per image. This could be due to the fact that the estimated cylinder qualities from ridge clarity maps are not discriminating enough among different parts of the images in this category, thus being not sufficiently informative regarding the automatic identification task.

6. Conclusions

Latent fingerprint matching is a biometric technique widely used in forensic applications, while it is still far from being reliable using fully automatic systems. In this paper, we combine the modern MCC based matching technique with objective local quality measures for the latent fingerprint images. We proposed a method to estimate the cylinder quality measures directly from fingerprint quality maps, in particular ridge clarity maps, by averaging the ridge clarity within the cylinder area and also taking into account the number of minutiae involved. The experiments on the NIST SD27 database showed that incorporating the estimated cylinder quality measures through the quality-based relaxation approach proposed by the authors in [9] can improve the identification performance for latent fingerprints in the Ugly category, while being not so effective for the Good category. It is however to be expected since the cylinder qualities in the Good category vary less than in the other categories, and thus there is not much to be gained there by using the proposed weighting method.

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