Enhancements to Latent Fingerprints in Forensic Applications

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***Abstract*—Latent fingerprint identification is a challenging task in criminal investigation due to the poor quality of ridge impressions and less region of interest on the fingerprint. In this paper, we propose a semi-automated latent fingerprint identification to markup fingerprint landmarks manually using the image enhancement filters which will improve the identification performance in lights-out mode. It uses the global and local adaptive binarization, and global minutia features with ISO/IEC 19794-2 standard fingerprint templates. In the latent fingerprint identification, the fingerprints are matched with rolled fingerprint database from standard law enforcement database. Also, the latent fingerprints are matched with the plain fingerprints database from the data collected using three different live-scanners. The efficacy of the proposed latent fingerprint identification systems is demonstrated on the standard NIST SD-27 (special database-27) latent prints database.**

***Index Terms*—latent fingerprints; ISO/IEC 19794-2 format; identification; emboss filter; sobel filter**

I. Introduction

Fingerprints play an important role in forensic analysis for criminal identification using the clues collected from the crime scene. Eventhough, fingerprint-based identification has been known and used for a very long time [1], it is still challenging task in criminal investigation. The latent prints are the fingerprints which are collected by leaving the finger impressions formed with sweat from fingers. The latent prints have the poor quality of ridge impressions and partial fingerprint area which need ridge enhancements to identify the suspects. As shown in figure 1, there are three different types of finger acquisition, namely, rolled, plain and latent prints. The rolled fingerprints can be acquired by placing the fingerprint on the fingerprint sensor surface and moving it from nail to nail. The plain fingerprints can be captured by simply placing the fingerprint on the sensor surface. The latent fingerprints can be collected from the scene of crime as part of the forensic analysis. The automatic extraction of genuine minutia points from the latent fingerprints becomes difficult due to low fingerprint quality and less area of interest on the fingerprint image.

The manual latent identification process, also known as ACE-V procedure [2] consists four steps, namely, analysis, comparison, evaluation, and verification.

1) Analysis: Assessment of quality of latent fingerprint and identification of the ridge and minutia information can by done by a human expert.
2) Comparison: Determines the similarity or dissimilarity of fingerprint landmarks using three levels of fingerprint features (Level 1, Level 2, and Level 3) with a referent rolled/plain fingerprint.
3) Evaluation: Decides whether the fingerprint pair is a match or non-match.
4) Verification: Re-examination of the results by another human expert to verify the results of the first human expert.

(a) (b) (c)

Fig. 1. Different fingerprint types: (a) rolled (b) plain and (c) latent prints

The majority of the algorithms developed for automated fingerprint matching are based on minutiae [3], [4] and [2]. Several recent studies on fingerprint matching have focused on the use of local minutiae descriptors [5], [3], [6], [7]. Some algorithms combine ridge orientation with minutiae information either at feature level by including ridge orientation information in local minutiae descriptors [8], [9] or at score level by combining scores from minutiae matching and global orientation field matching [9], [10]. The latent matching accuracy is improved by using the features which are located manually from the latents' [11], [12], [13], [14]. 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. However, only a small portion of latents can be correctly identified using this approach. There have also been some studies on fusion of multiple matchers [15] or multiple latent prints [4]. NIST has been conducting a multi-phase project on Evaluation of Latent Finger-print Technologies (ELFT) to evaluate latent feature extraction and matching techniques [16]. Jain et. al. have proposed a latent matcher for automatic identification of suspects by using the extended features, namely, singularity, ridge quality map, and ridge flow map[17], [18]. The latent fingerprint image quality is measured by Spectral Image Validation and Verification (SIVV)-based metric [19] and the latent fingerprint image quality (LFIQ) metric based on triangulation of minutiae points[20].

In this paper, we proposed a semi-automated latent fingerprint identification system which uses different imaging filters to enhance the latent print. The semi-automated latent fingerprint identification system is more flexible for fingerprint forensics experts which would allow them to acquire fingerprint latents captured with various devices from crime scenes, falsified documents etc.

The rest of the paper is organized as follows: Section II, discusses the details of semi-automated latent fingerprint identification system. Experimental results of the proposed latent fingerprint identification systems are discussed in section III. Conclusions are explained in section IV.

II. Semi-automated Latent Fingerprint Identification

The proposed semi-automated latent fingerprint identification system consists of different phases, namely, fingerprint acquisition, finger markup & matching, results review and evidence exhibits. The phases involved in the latent fingerprint recognition system are explained in the following sections.

A. Image acquisition

Images can be acquired through a control capture device such as a scanner or a fixed focus camera. The image acquisition provides a perceived *dpi* (dots per inch) measurement to adjust the image resolution. The image *dpi* captured using a live-scanner is different from the image which is collected from the scene of crime. Typically, latent fingerprint examiners tend to follow a practice of placing a physical scale next to the latent fingerprint being photographed to give an idea to the user as well as systems to relate to the actual size of the real latent. The *dpi* measurement tool allows the system to determine the perceived *dpi* of the image using the ridge pitch or the distance between each fingerprint ridge. The latent fingerprint can be scaled up/down to the default fingerprint resolution, i.e., 500*dpi*, which improves the matching accuracy at later stage.

B. Image markup

Image markup allows to analyze and markup fingerprint landmarks. The markup provides image processing filters to enhance the image and to compose the desired effect by layering various filters like sobel filter [21], emboss filter [22], lighting filter [21] and fingerprint skeletonization [23]. Basic image manipulations such as rotation and flipping are useful to trace the landmarks on the image. A set of tools to specify fingerprint landmarks are implemented which uses the proposed latent fingerprint recognition algorithm to automatically generate markup points which can be accepted by the user as valid points.

C. Matching

The proposed fingerprint matching algorithm uses ISO/IEC templates [24]. The feature vector consists of the information; x-y coordinates, direction, type and quality of each minutia. Each edge consists of the information like the edge distance and directional difference between minutiae. The proposed algorithm is of rotation and translation invariant. The following are the steps involved in the global and local minutia matching algorithm which is summarized in Algorithm 1.

Algorithm 1 : Latent fingerprint matching algorithm

Inputs: Query and reference ISO/IEC fingerprint templates.
Step 1. Get the details of each minutia from the template information, namely, x-y coordinates, direction, type and quality.
Step 2. Compute the edge pair information for each minutia to all other minutia.
Step 3. Sort the edge pair information using distance.
Step 4. Compute the edge pair information for each minutia to all other minutia.
Step 5. To remove false matched minutia pairs, the matched minutia pairs are validated with all other matched minutia pairs.
Step 6. Compute the matching score.

D. Result review / Adjudication

The biometric recognition system allows few errors in the identification process. In order to reduce the errors, fingerprint experts look for possible fingerprint matches and enhance the fingerprints to compare the minutia features manually using fingerprint adjudication process. Fingerprint adjudication means, comparison of two fingerprints side-by-side to analyze the matched minutia features. Once encounters are returned as search result which allows to view the probe as well as the encounter candidate, side by side, with a template overlay. There is a match point highlight capability to view the actual matching landmarks on the system. A set of filters allow the user to enhance the images. The end objective is to allow the user to make the decision and call one or multiple encounters as 'hit' for a particular case. The hit cases may be subjected to a peer review depending on the deployment scenario.

E. Evidence exhibit / reporting

Once a set of encounters are marked as hit, the system generates an evidence exhibit, detailing images matching regions. Figure 2 illustrates the sample of evidence reporting for a particular matched fingerprint pair. The left side image is known as probe fingerprint or latent print and the right side image is known as candidate fingerprint or plain/rolled fingerprint. The matched regions are illustrated in circles.

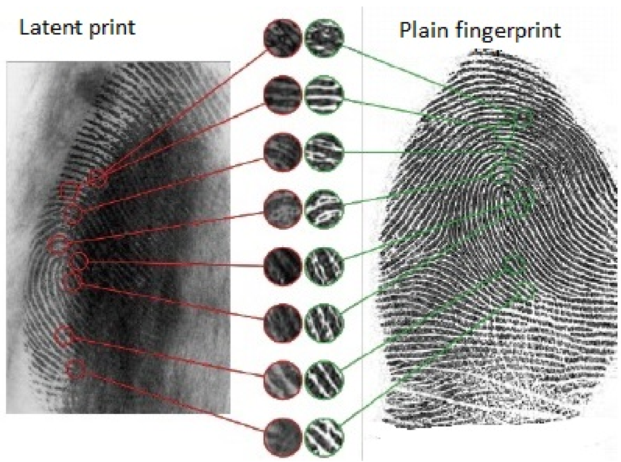

Fig. 2. Evidence exhibit of a particular matched fingerprint pair

III. Experimental results

The experimental results of latent fingerprint recognition are presented in lights out mode. The standard NIST special database 27 [25] is used for the experiments which contains latent fingerprints and their corresponding rolled fingerprint mates. There are 258 latent cases, each case includes the latent image and the corresponding ten print image. The database is divided into three groups LF-1, LF-2 and LF-3, where the fingerprint qualities are good, bad and ugly, respectively. There are 88 latent prints in LF-1 group, 85 latent prints in LF-2 group and 85 latent prints in LF-3 group in SD27 database. Each image is of size 800x768 pixels and stored in an uncompressed format. All the images are formatted using the ANSI/NIST-ITL 1-2000 standard [26] and Type-1, 13, & 14 records.

The ISO/IEC 19794-2 templates are generated from latent and rolled fingerprints and then submitted for matching. The latent prints were matched against the plain prints of 1758 images which are collected using three different live-scanners (Biomini, Cogent and Upek) and the existing rolled fingerprints from the SD27 database. The plain fingerprint data consists of all the 10 fingerprints of 30 subjects captured at 5 different instances. The proposed fingerprint matching algorithm is evaluated and compared with NIST Bozorth algorithm. The same algorithm is used for the proposed semi-automated latent fingerprint identification system. Figure 3 illustrates the performance of Bozorth fingerprint matcher algorithm using four different scenarios of data. Similarly, in Figure 4 presents the performance of proposed fingerprint matcher algorithm using the four different scenarios of fingerprint data. We observed that the proposed algorithm gives good performance even with the fingerprint images captured using the cross-sensor fingerprint authentication devices.

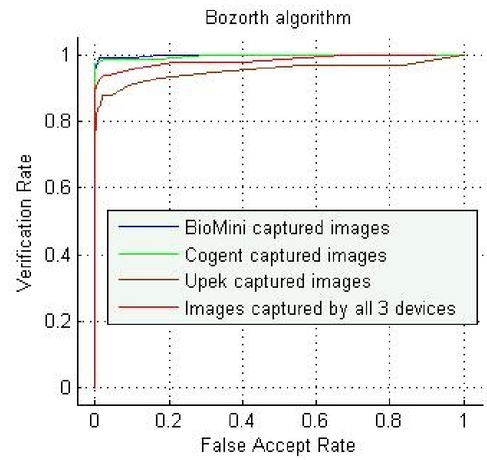

Fig. 3. Analysis on Bozorth matcher using the images captured by all the three devices

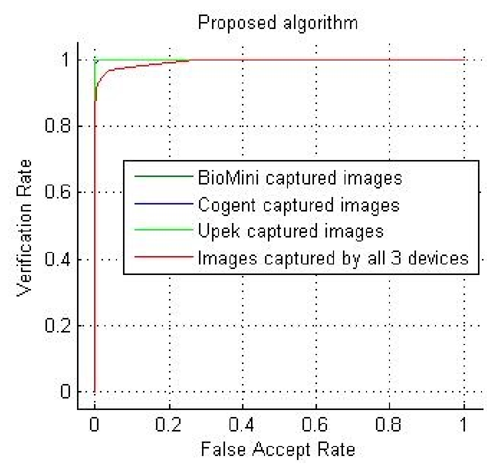

Fig. 4. Analysis on proposed matcher using the images captured by all the three devices

As shown in table I, the matching accuracy is better in the group of LF-1 latent fingerprints where 60% of the cases are identified in top 10 of search results, 30% of the cases are identified in top 100 search results and around 10% are not identified. Similarly in LF-2 latent fingerprints are identified around 40% in top 10 search results, 30% in top 100 search results; and the remaining cases are not identified. LF-3 latent fingerprints around 70% are not identified. Figure 5 shows the CMC curves of the automated latent fingerprint identification for LF-1 (Good), LF-2 (Bad), and LF-3 (Ugly) quality latent prints. It is observed that the matching performance for LF-1 group quality latents is significantly improved when compared with the latent fingerprints belonging to the other two groups LF-2 and LF-3.

The unsolved latent fingerprints need an experts' manual

TABLE I
RESULTS OF LATENT FINGERPRINT MATCHING

Latent-Group	Top 10 (%)	Top 100 (%)	Not in Top 100 (%)
LF-1 (Good)	60	30	10
LF-2 (Bad)	40	30	30
LF-3 (Ugly)	10	20	70

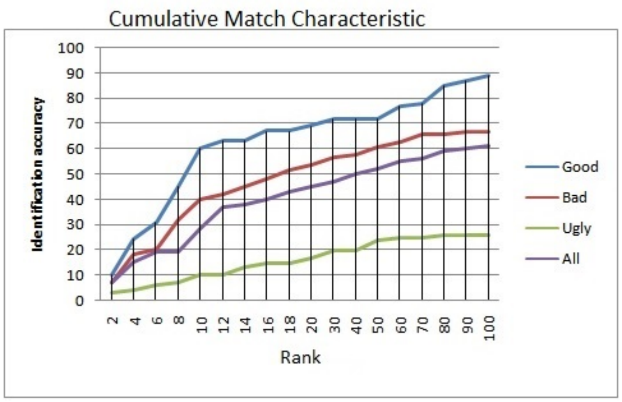

Fig. 5. CMC curves for different quality latent prints (good, bad, and ugly)

intervention with semi-automated latent fingerprint identification system. As shown in figures 6 & 7, The latent fingerprints are enhanced to submit in semi-automated identification system using the image processing filters, namely, sobel, lighting, emboss and color filters. Figure 6(a) is the portion of a sample latent print. The region of interest on latent print is located as illustrated in figure 6(b). Figures 6(c) and 6(d) illustrate the image enhancements using color, brightness and contrast adjustments. The sobel filter applied on the image with gradient directions 0^0, 90^0, 180^0 and 270^0 are shown in the figures 6(e), 6(f), 6(g) and 6(h), respectively. The emboss filter applied on the image with gradient directions 0^0, 90^0, 180^0 and 270^0 are shown in the figures 7(a), 7(b), 7(c) and 7(d), respectively. Similarly, the sobel filter applied on the image with gradient directions 0^0, 90^0, 180^0 and 270^0 are shown in the figures 7(a), 7(b), 7(c) and 7(d), respectively. There is no specific reason of choosing these filters with different parameters like gradient direction and filter size to highlight the ridge patterns but observed the improvements in ridge information empirically. The ridge information may still improve if we use different filter enhancements. After these enhancement, the ridge information is highlighted to easily distinguish the hidden minutia points on the latent fingerprint image. It is observed that the rank-1 identification rate for all the latents improved to 79% (LF-1 (87%), LF-2 (78%) and LF-3 (72%)) after the latent fingerprint enhancements using the semi-automated latent fingerprint identification system. The results are compared with the existing method proposed by Anil K Jain et. al. [17] and observed the improvement in rank-1 identification rate as shown in Table II with the assumption that it will not be a big difference in the identification rate even if we add 1758 images to SD27 dataset.

TABLE II
COMPARISON OF RANK-1 IDENTIFICATION RATE

Latent-Group	Anil K Jain et. al. [17] (%)	Proposed method (%)
LF-1 (Good)	83	87
LF-2 (Bad)	74	78
LF-3 (Ugly)	65	72

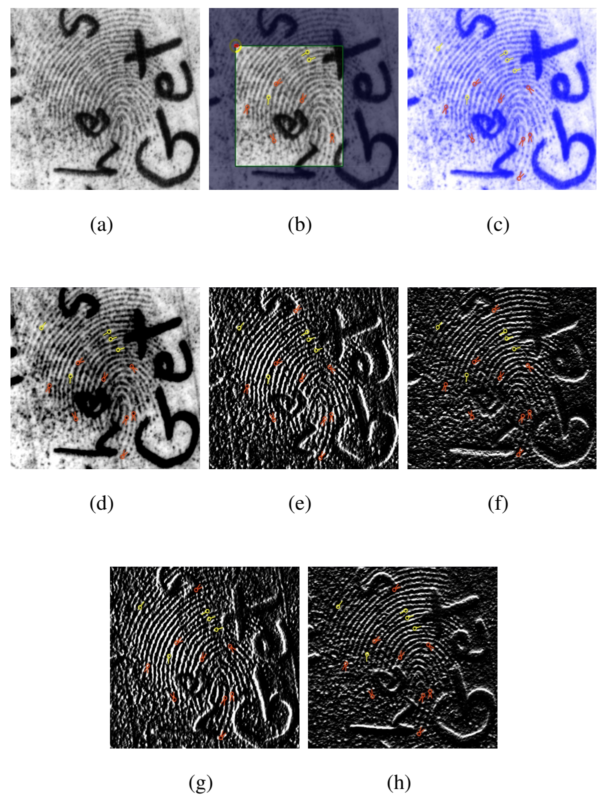

Fig. 6. Finger markup filters: (a) sample latent print from NIST SD-27, (b) region of interest marking, (c) enhance image with color filters, (d) brightness and contrast enhancements, (e) sobel filter applied with gradient direction 0^0, (f) sobel filter applied with gradient direction 90^0, (g) sobel filter applied with gradient direction 180^0, (h) sobel filter applied with gradient direction 270^0.

IV. CONCLUSION

In this paper, a semi-automated latent fingerprint identification system is proposed in lights-out mode where the standard ISO/IEC 19794-2 templates are considered. The proposed approach reduces the manual intervention of the fingerprint experts in identifying the suspects. The semi-automated latent fingerprint identification system have the image enhancement filters, namely, sobel, emboss, and lighting. The matching performance for LF-1 group latent prints is significantly better than those for the latent prints

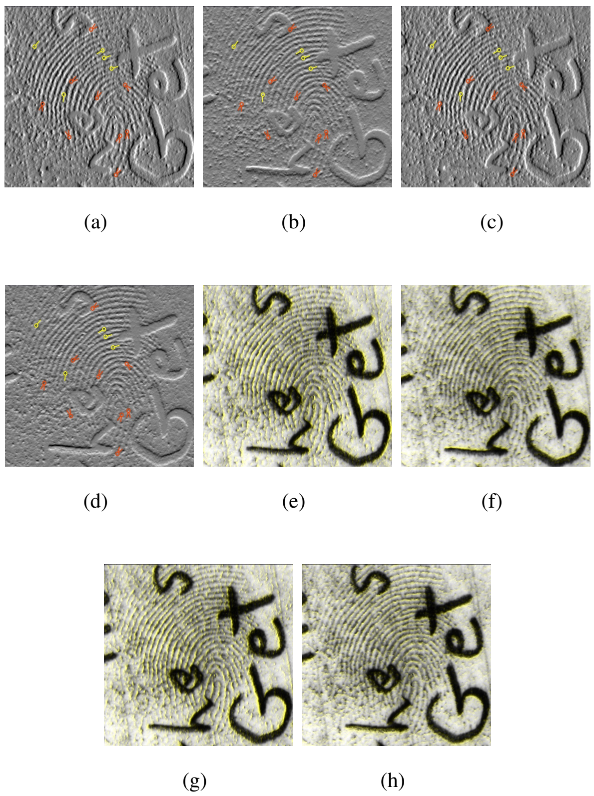

Fig. 7. Finger markup filters: (a) emboss filter applied with gradient direction 0^0, (b) emboss filter applied with gradient direction 90^0, (c) emboss filter applied with gradient direction 180^0, (d) emboss filter applied with gradient direction 270^0, (e) lighting filter applied with gradient direction 0^0, (f) lighting filter applied with gradient direction 90^0, (g) lighting filter applied with gradient direction 180^0, (h) lighting filter applied with gradient direction 270^0.

belonging to the other two groups LF-2 and LF-3. The rank-1 identification rate for all the latents is improved to 79% after the latent fingerprint enhancements using the semi-automated latent fingerprint identification system.

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