Enhancing Latent Fingerprints on Banknotes

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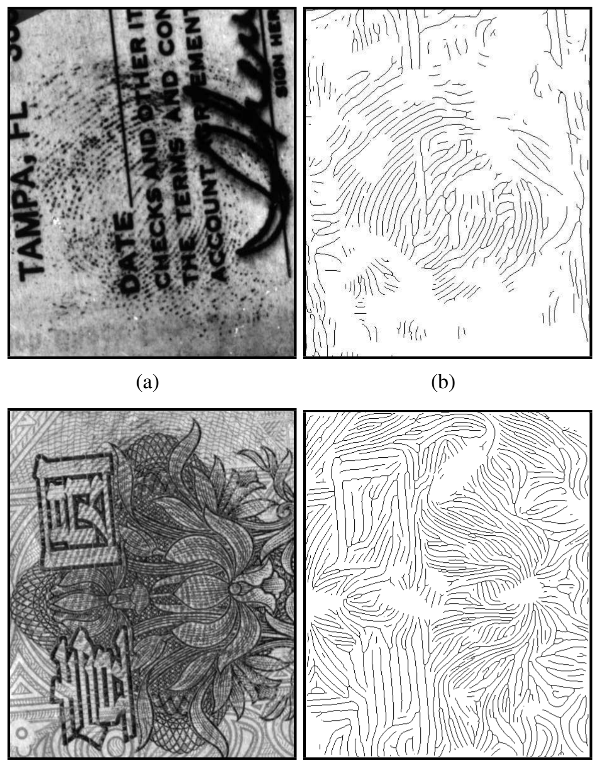
Abstract

Matching unknown latent fingerprints lifted from various objects or surfaces at crime scenes to fingerprints of known subjects is of vital importance for law enforcement agencies to identify suspects. Banknotes are one of the most common objects containing valuable latent fingerprints. However, due to the complex pattern printed on banknotes, it is a challenging problem even for human experts to mark minutiae in such fingerprints. In this paper a novel technique is proposed to enhance fingerprints on banknotes so that they can be successfully identified by existing fingerprint matchers. The proposed algorithm is based on subtraction of the reference orientation in reference banknote, which is registered to the latent fingerprint by a coarse-to-fine registration algorithm. Promising results are reported on a database which contain 192 latents on banknotes, which proves the effectiveness of the proposed algorithm.



(a) (b) (c) (d)

Figure 1. (a) A latent fingerprint on a check; (b) the ridge skeleton image of (a) obtained by a well-known commercial fingerprint matcher, VeriFinger 6.2 SDK [1]; (c) a latent fingerprint on a banknote; (d) the ridge skeleton image of (c) obtained by VeriFinger. Due to the complex background patterns, VeriFinger misses many genuine ridges and produces many spurious ridges.

1. Introduction

Fingerprint is the most popularly and successfully used trait in biometric recognition. Driven by the increasing concerns on security, the decreasing cost of hardware, and the rapid development of fingerprint recognition algorithms, fingerprint recognition has been applied to various fields ranging from forensics to individuals, such as crime investigation, airport security, attendance, payment, access control and computer login [18]. The pervasive application of fingerprint recognition technology causes a misconception that fingerprint recognition is a fully solved problem. In fact, there are still some quite challenging problems worthy of study, including small finger area, distorted fingerprints, latent fingerprints, etc. Among them, latent fingerprint recognition is receiving more and more attention because of its crucial role in identifying criminals and terrorists [16].

Latent fingerprints (or simply latents) are friction ridge impressions left unintentionally on objects or surfaces at crime scenes. Such impressions are called “latent” because they are usually not directly visible to the naked eye. Various physical or chemical techniques are required to enhance the latent fingerprints so that they become visible [6]. However, even after physical or chemical enhancement, the quality of the fingerprints is usually still so poor that automatic fingerprint recognition algorithms cannot reliably extract and match minutiae, the most distinctive features in fingerprints. An extremely challenging problem for fingerprint recognition algorithms is the complex background of many latents. Fig. 1 shows two latent fingerprints with complex background and their ridge skeleton images obtained by a well-known commercial fingerprint recognition algorithm, VeriFinger 6.2 SDK [1]. As we can see from the extracted ridge skeleton images, VeriFinger performs poorly in the first latent whose background is a check and totally fails in the second latent whose background is a banknote.

Banknotes are one of the most common objects containing valuable latents. For example, latent fingerprints on stolen or robbed cash can be used to identify the suspects and latent fingerprints on counterfeit banknotes can be used to identify the counterfeiters [9]. As a result, forensic researchers have developed physical or chemical techniques to develop latents on banknotes [17, 14, 9, 3]. Although latent development techniques can improve the visibility of latent fingerprints, the complex background pattern still exists. The existence of such background pattern is an extremely challenging problem not only for automatic fingerprint matchers but also for human fingerprint experts. As told by several fingerprint experts, since it is very time-consuming, tedious and prone to error to manually mark the minutiae in fingerprints with banknote background, law enforcement agencies process latents on banknotes only in very serious cases. One way to solve this problem is to design an automatic latent feature extraction and matching system which can match such latents to gallery fingerprints efficiently and accurately.

Although there exist a number of fingerprint enhancement algorithms [18] and a few recent algorithms [21, 7, 12, 13] are especially designed for enhancing latents, they are not sufficiently robust to process latents on banknotes due to the very complex background patterns. Since automatic latent segmentation is a very challenging problem, these latent enhancement algorithms require manually marked fingerprint region mask, which is inconvenient. Although several interactive latent enhancement algorithms should be able to process latents on banknotes [5, 22], they require even more user inputs and the current trend in the latent fingerprint community to make the enhancement algorithm fully automatic [11].

Since each country has only a few different banknotes in circulation, a straightforward method to enhance latents on banknotes is to use the well-known background subtraction in the video processing area. Such an approach was described by Dalrymple [10]. However, this method only works when the reference banknote and the banknote containing the latent are of the same quality, captured on the same lighting condition, and can be exactly registered with each other using a global rigid transformation model. These requirements are hard to meet in practice for two reasons. Firstly, due to everyday wear and tear, the banknote containing latents and the reference banknote can be very different in appearance. Secondly, because the various patterns on banknotes are printed in multiple stages and thus the relative position between different patterns is not exactly the same in different banknotes of the same denomination [20].

In this paper, a novel latent fingerprint enhancement algorithm is proposed to enhance latents on banknotes so that such fingerprints can be successfully matched by existing fingerprint matchers. By comparing the major frequency components obtained through local orientation estimation in local regions of the latent image and the reference banknote, which is registered to the latent image by a coarse-to-fine registration algorithm, local ridge orientation of the fingerprint can be detected. Then the Gabor filtering technique can be used to enhance the latent. The proposed algorithm is fully automatic and can deal with banknotes in poor condition. Matching experiments were conducted on a database consisting of 192 latent fingerprints with 1 yuan banknote background and 27,000 rolled fingerprints from the NIST SD14 database [2]. Compared with three other fingerprint enhancement algorithms [1, 10, 13], the proposed algorithm achieved the highest rank-1 rate, demonstrating the effectiveness of the proposed algorithm.

The rest of the paper is organized as follows. Section 2 presents the proposed approach. Section 3 gives the experimental results. Finally, we summarize the paper and discuss future research directions.

2. Proposed approach

Given the image of a partial banknote, which contains a latent fingerprint, the proposed latent fingerprint enhancement algorithm outputs the enhanced fingerprint image, where the ridge structure is enhanced and the background is removed. The flowchart of the proposed algorithm is shown in Fig. 2 and its four modules are summarized as follows:

1) Local orientation estimation: Local Fourier analysis is used to find several strongest orientation elements in each block of the reference banknote and the latent. Local orientation estimation for the reference banknote can be performed offline to save time.

2) Coarse-to-fine registration: First, the reference banknote is coarsely registered to the latent by matching block-wise orientation fields. Then the corresponding part of the reference banknote is finely registered to the latent by matching pixel-wise gradient fields.

3) Fingerprint orientation field estimation: By comparing the orientation elements in corresponding blocks of the registered reference banknote and the latent image, orientation elements corresponding to fingerprint are found and a smoothing step is performed to regularize the fingerprint orientation field.

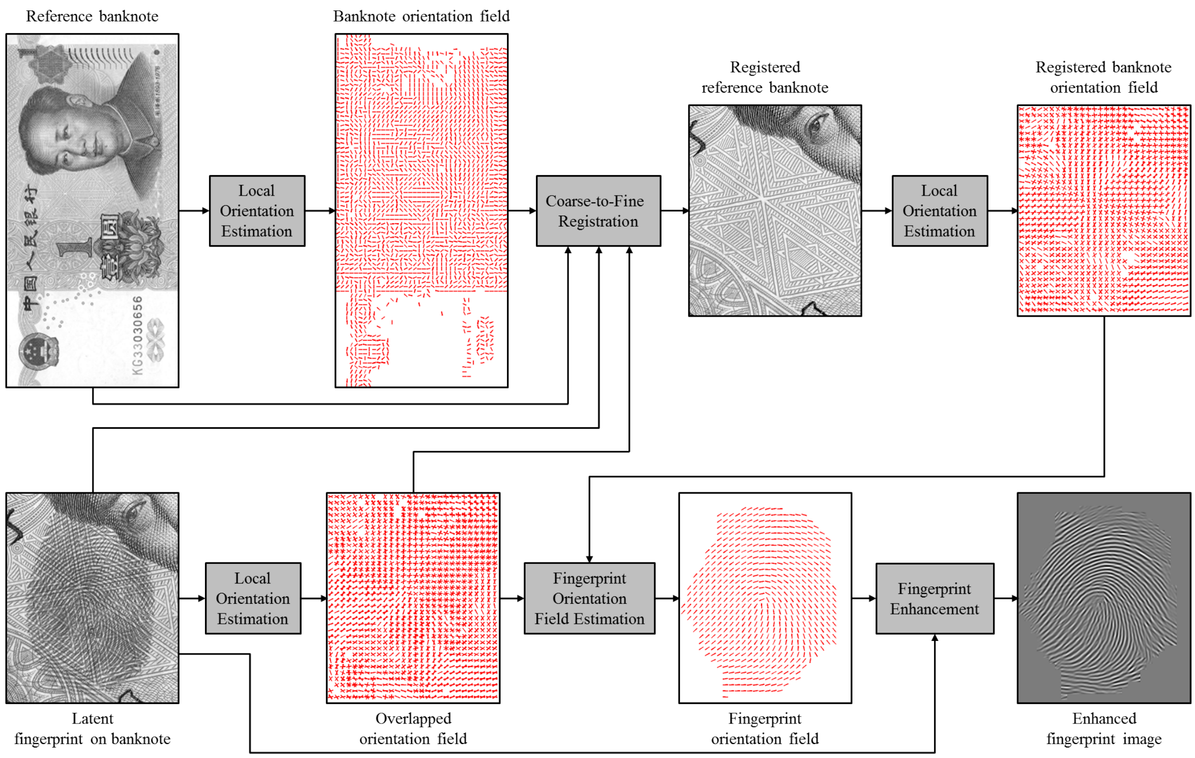


Figure 2. Flowchart of the proposed latent enhancement algorithm.

4) Fingerprint enhancement: Gabor filter tuned to local ridge orientation and frequency is used to enhance the latent fingerprint.

The details of these modules are given below.

2.1. Local Orientation Estimation

In good quality fingerprints, ridges flow continuously and adjacent ridges are well separated. For such fingerprints, local ridge orientation can be reliably estimated using local image information by existing methods, such as gradient-based method [4], slit-based method [19], or short-time Fourier transform (STFT) [8]. However, in the case of latent fingerprints on banknote, various texture patterns overlap with the fingerprint ridge pattern and thus local information alone is not sufficient for estimating ridge orientation. In the case of good quality fingerprint, there is a pair of peaks in the magnitude spectrum, while in the case of latent fingerprint, multiple pairs of peaks exist. In the case of latents, the magnitude of the peaks corresponding to fingerprint ridges is not necessarily the strongest. This is the most challenging problem for latent fingerprint feature extraction. In the case of latents on banknote, the fortunate thing is that a reference banknote is available. So we can compare the magnitude spectrums of a local region in the latent and the corresponding region in the reference banknote and assume that the additional peaks correspond to fingerprint ridges. This idea is illustrated in Fig. 3. Here we assume that two banknotes (the banknote containing the latent and the reference banknote) have been aligned with each other. The registration algorithm will be described later.

Table 1. Some Symbols in Algorithm 1

Symbol	Description
$\boldsymbol{\theta}$	the set of candidate orientation(s)
θ_i	one of candidate orientation(s)
n_c	the number of candidate orientation(s)
F	the results of Discrete Fourier Transform of input image
m	the number of the selected local maxima
ϕ_j	one of orientations of m local maxima in F
a_j	the corresponding magnitude of ϕ_j
t_1, t_2, t_3	three threshold values

The purpose of local orientation estimation algorithm is to detect a set of candidate orientations in each 16×16 block of the image. The pseudo code of this algorithm is given in Algorithm 1 and some symbols are defined in TABLE 1.

The algorithm is summarized here. It takes a local image

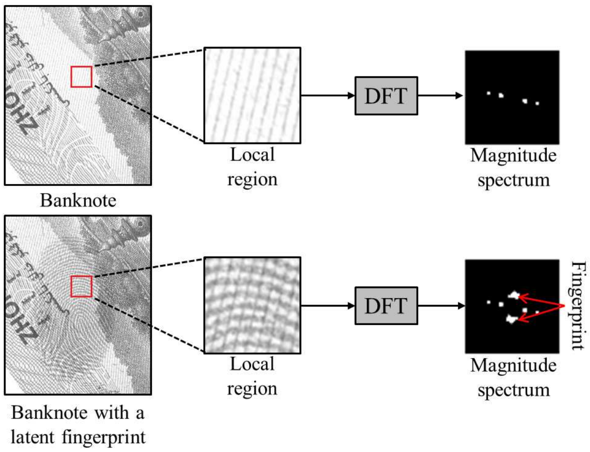


Figure 3. Magnitude spectrum of a local region in a banknote and the magnitude spectrum of the corresponding region in another banknote containing a latent fingerprint. The additional pair of peaks in the bottom magnitude spectrum corresponds to fingerprint.

of 64×64 pixels around the block of 16×16 pixels as input and outputs a set of candidate orientations. First, Discrete Fourier Transform (DFT) is calculated for the local image. Then we detect a set of local maxima in the magnitude spectrum. Finally, a set of at most n_{c} orientation elements satisfying some criteria is chosen. The local orientation estimation algorithm is also used to estimate the orientation field of the full banknote and the orientation field of the registered partial banknote (see the flowchart in Fig. 2). While the algorithm is the same, the parameter n_{c}, the number of candidate orientation(s), is different for three cases.

$$n_{\mathrm{c}} = \begin{cases} 1, \text{Reference banknote} \\ 3, \text{Registered partial reference banknote} \\ 4, \text{Latent.} \end{cases} \quad (1)$$

The three threshold values are empirically set as $t_1 = 6$, $t_2 = 0.2$, $t_3 = 10^\circ$.

2.2. Coarse-to-fine Registration

In order to determine local ridge orientation of the latent fingerprint, the reference banknote needs to be aligned to the latent image using a suitable search technique. The simplest technique is to exhaustively try all possible alignments, i.e., to do a full search. Because of the large image size of banknote, a coarse-to-fine registration algorithm is developed. The coarse registration is based on block-wise orientation field and the fine registration is based on pixel-wise gradient field.

In coarse registration, we seek the optimal rotation and translation between the orientation field of reference banknote and the orientation field of the latent. For each possible rotation and translation parameter, we compute a similarity score between the two orientation fields, which are aligned with each other using the current transformation parameters. The similarity score is defined as the ratio of the number of similar orientation elements to the number of orientation elements in latent. A pair of orientation elements is said to be similar if their difference is less than 10°. The transformation producing the largest similarity score is determined as the optimal transformation.

Input: Local image I of size 64×64 pixels
Output: Candidate Orientation(s) $\Theta = \{\theta_i\}$
$\Theta \leftarrow \emptyset$;
$F = \mathrm{DFT}(I)$; //Compute the Discrete Fourier Transform of I
$\{(\phi_j, a_j)\}_1^m = \mathrm{FindLocalMaxima}(F)$;//Compute the orientations ϕ_j and magnitudes a_j of m local maxima in F
Sort $\{(\phi_j, a_j)\}_1^m$ in descending order of a_j;
for $j = 1, \cdots, m$ **do**
  if $a_j < t_1$ *or* $a_j/a_1 < t_2$ **then**
    break;
  end
  if *the minimum difference between* ϕ_j *and all candidate orientations in* Θ *is bigger than* t_3 **then**
    Add ϕ_j to Θ;
    if $|\Theta| == n_c$ **then**
      return;
    end
  end
end

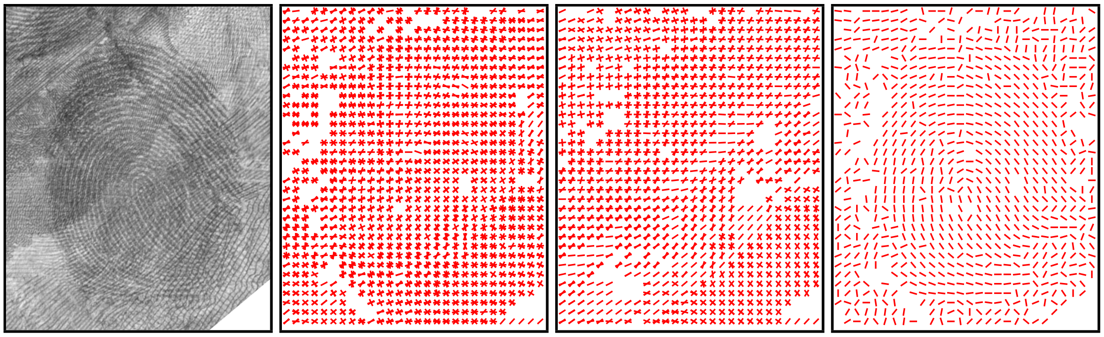
Algorithm 1: Local Orientation Estimation.

Because the patterns in banknotes are printed in multiple stage, different patterns in two different banknotes cannot be simultaneously aligned using a global rigid transformation. Thus we segment the latent into non-overlapping blocks of size 64×64 pixels and then for each block, search for the most similar block in the reference banknote which has been coarsely aligned with respect to the latent. Then we combine all corresponding blocks in the reference banknote to get the partial reference banknote which is finely registered with respect to the latent.

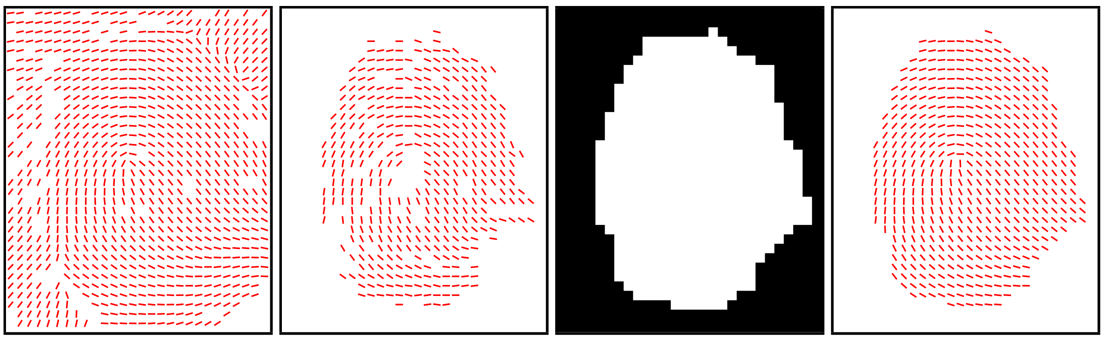
For fine registration, the similarity score between two blocks is defined as follows:

$$s = \sum_{\mathbf{x}} G_{\mathrm{L}}(\mathbf{x}) \cdot G_{\mathrm{R}}(\mathbf{x}), \quad (2)$$

where $\mathbf{x} = (x, y)$ denotes a pixel, and G_{L} and G_{R} are the pixel-wise normalized gradient fields of the latent block and the reference block, respectively.

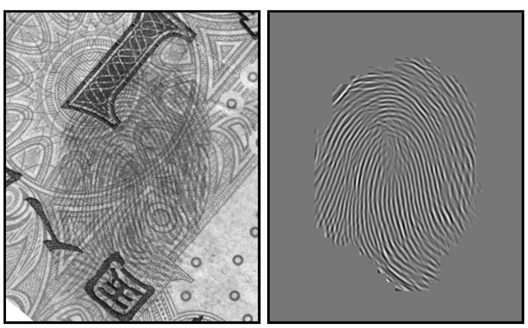


(a) Latent fingerprint (b) Overlapped orientation field (c) Reference orientation field (d) Chosen orientation elements



(e) Smoothed orientation elements (f) Reliable orientation elements (g) Fingerprint region (h) Reconstructed orientation field

Figure 4. Estimating the orientation field of a latent fingerprint on banknote.



(a) Latent fingerprint (b) Enhanced fingerprint

Figure 5. Latent fingerprint and its enhanced result.

2.3. Fingerprint Orientation Field Estimation

We estimate local ridge orientation of the latent fingerprint by comparing the candidate orientations in each block of the latent with the orientations in the corresponding blocks of the registered reference banknote. If the difference between one of candidate orientations in the latent block and any orientation in the corresponding reference block exceeds a predetermined threshold $5°$, we will decide this candidate orientation to be the local ridge orientation. If no orientation in a latent block is significantly different from the orientations in the corresponding reference block, this block is deemed as a background block.

The orientation field obtained using this approach may be very noisy. Hence we perform the following steps to obtain a good quality orientation field:

1) The orientation field is smoothed using a Gaussian filter with $\sigma = 3$ [18]. Thanks to irregularity of noise, the orientations in noisy areas will be adjusted greatly (for example, more than $20°$) by the smoothing operation. We remove such blocks and set the largest 4-connected component of the remaining blocks as the fingerprint region, which contains reliable orientation elements.

2) The holes in the fingerprint region is filled using the morphological closing operation, namely first morphological dilation and then erosion.

3) Orientations in the holes are estimated by the orientations in neighboring blocks by interpolation.

An example is given in Fig. 4 to show the intermediate steps of estimating fingerprint orientation field.

2.4. Fingerprint Enhancement

With the orientation field of a latent, we employ the well-known Gabor filtering technique to enhance the fingerprint ridge structures and remove the background patterns [15]. Another important parameters of Gabor filtering, the

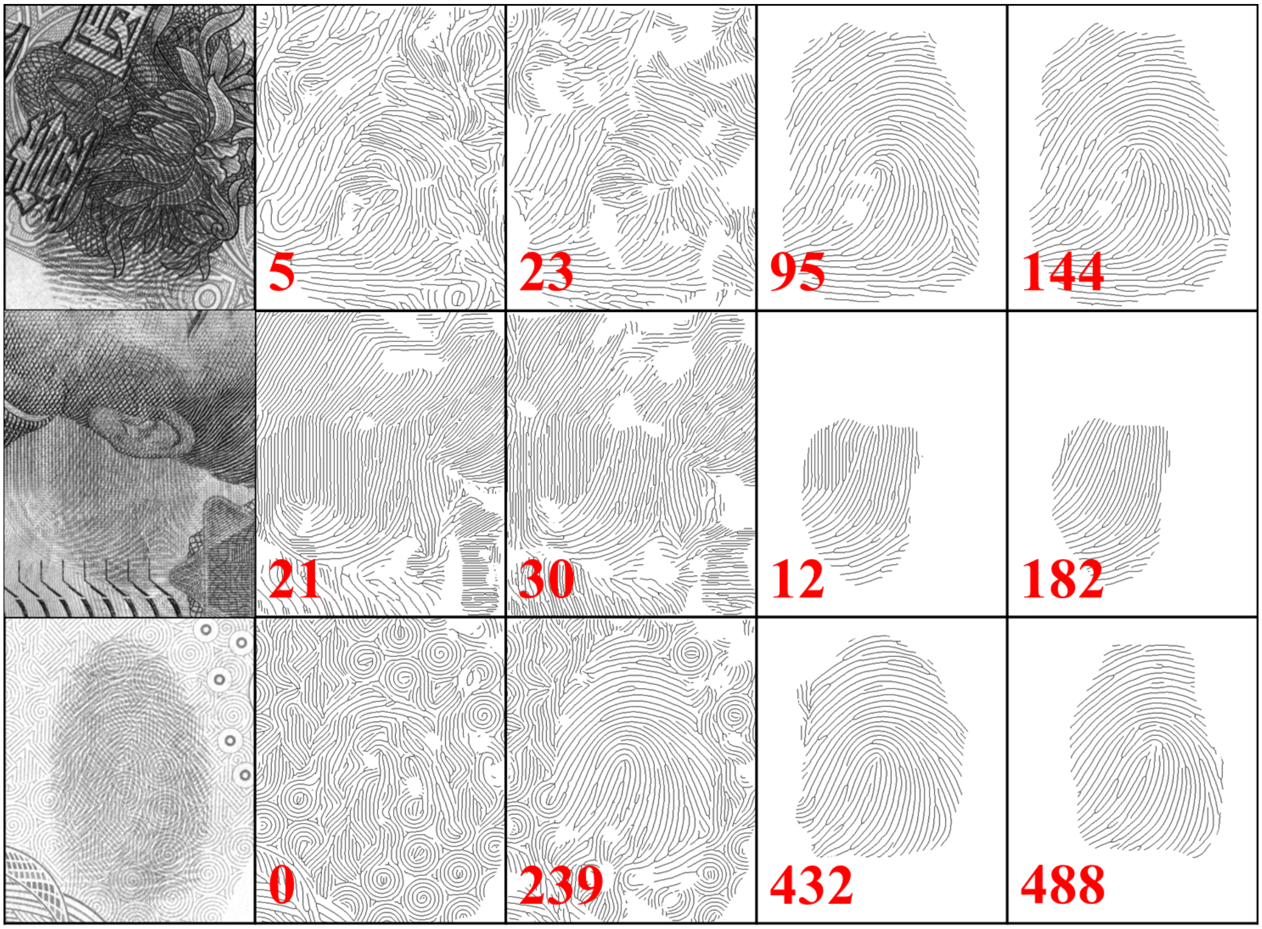


Figure 6. Results of four enhancement algorithms for three latent fingerprints. From left to right: latent fingerprints, skeleton images obtained by VeriFinger, skeleton images obtained by background subtraction algorithm [10], skeleton images obtained by the dictionary based algorithm [13], and skeleton images obtained by the proposed algorithm. The match scores between the template fingerprints and the skeleton images obtained by the four algorithms are overlaid on the skeleton images.

block-wise ridge frequency map is calculated using the x-signature method in [15]. As we can see from the example in Fig. 5, the banknote pattern has been successfully removed in the enhanced fingerprint image.

3. Experiment

3.1. Dataset

Since there are no public domain databases of latent fingerprints with banknote background, we collected a database called Tsinghua Banknote Latent Fingerprint Database. Note that latents on Banknotes can be developed by various techniques, such as dusting fuming, iodine fuming, ninhydrin fuming and so on. In our experiments, dusting technique is used. We obtained fingerprint samples using the following processes:

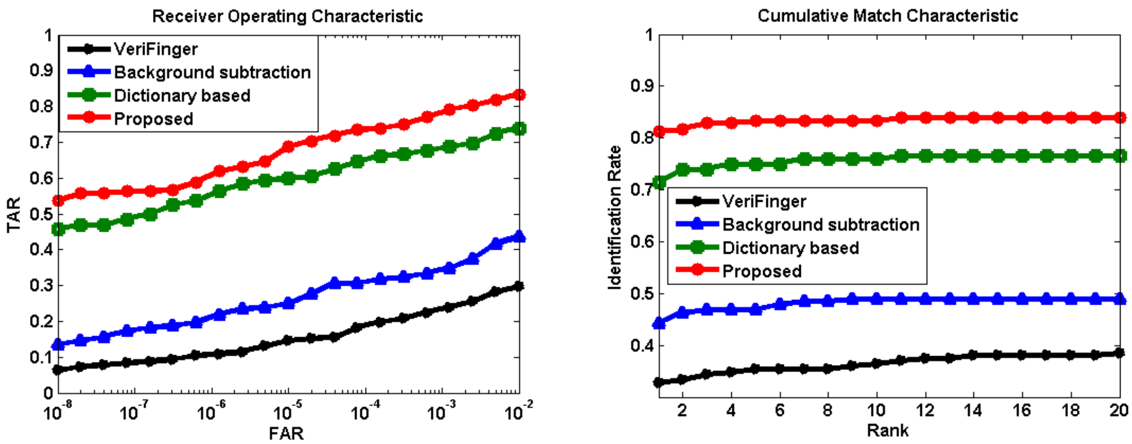
1. press the finger on a banknote;
2. develop the latents using black powder and brush;
3. convert the banknote into electronic version using a general purpose scanner.

A total of 192 latents were contributed by 16 different fingers. The template fingerprints of all these fingers were obtained using the ink-on-paper technique and scanned by the same scanner. All fingerprints in this dataset have a resolution of 500 ppi and all of them are grayscale images.

3.2. Qualitative Evaluation

We compare the enhancement results of the proposed approach with the results of VeriFinger 6.2 SDK, background subtraction [10], and the dictionary based approach [13] [1]. The dictionary based algorithm requires the region of inter-

[1] Available at http://ivg.au.tsinghua.edu.cn/index.php?n=Code.GlobalDict



(a) ROC curves

(b) CMC curves

Figure 7. The ROC curves and CMC curves of four fingerprint enhancement algorithms on the Tsinghua Banknote Latent Fingerprint Database. The results of VeriFinger [1], background subtraction algorithm [10], dictionary based algorithm [13], and proposed algorithm are presented together.

est of the latent, which is provided by the proposed algorithm. Fig. 6 gives some results of four approaches. From Fig. 6, we can see that:

- the proposed approach can obtain the region of fingerprints, but the other approaches cannot.
- in the fingerprint region, the proposed approach almost always enhance fingerprint ridges, while VeriFinger and background subtraction sometimes enhances background patterns and sometimes enhance fingerprint ridges.
- the match scores between the mated template fingerprints and the enhanced latents by the proposed algorithm are higher than the other three approaches.

3.3. Quantitative Evaluation

The purpose of enhancing the latents is to increase the match scores between latents and the mated template fingerprints. To quantitatively evaluate the contribution of the proposed latent enhancement algorithm to the matching accuracy, we conducted a matching experiment using 192 latents on 1 yuan banknotes. VeriFinger 6.2 SDK is used to match the enhanced fingerprint to the corresponding template fingerprint. Note that, only 192 genuine matches are executed because the output scores of VeriFinger are linked to the False Accept Rate (FAR). Fig. 7(a) shows the Receiver Operating Characteristic (ROC) curves of the four enhancement algorithms. From Fig. 7(a), we can clearly see that the True Accept Rate (TAR) of proposed algorithm is much higher than the TARs of the other three algorithms, demonstrating the contribution of the proposed fingerprint enhancement approach.

The Cumulative Match Characteristic (CMC) curve is commonly used to report latent matching accuracy. Since there are only 16 templates in our dateset, to make the experiment more realistic, we use all 27,000 fingerprints in the NIST SD14 database as the background database. A CMC curve plots the rank-k identification rate against rank-k, for $k = 1, \cdots, 20$. The rank-k identification rate indicates the proportion of times the mated fingerprint occurs in the top k matches. In this experiment, our algorithm achieves the highest rank-1 identification rate of 81.25%, much higher than the second best algorithm. The CMC curves of the four enhancement algorithms are given in Fig. 7(b).

The average time of the proposed algorithm (implemented in MATLAB) is about 1 minute on a PC with 3.30 GHz CPU. More specifically, the coarse registration, fine registration and enhancement takes about 40 seconds, 10 seconds and 15 seconds, respectively. The coarse registration step is very slow because we try all possible translation and rotation. In real applications, the operator can simply align the latent with respect to the reference banknote, leading to significant speedup. The algorithm can also be speeded up with proper optimization and C implementation.

4. Conclusions

In forensic applications, banknote is a very common carrier containing valuable latent fingerprints. However, extracting minutiae from latents on banknotes is extremely difficult due to the complex texture patterns in banknotes. As we have shown in this paper, even well optimized commercial fingerprint algorithm performs poorly on such latents. A fingerprint enhancement algorithm capable of processing latents on banknotes is very desirable. Although a general purpose fingerprint enhancement algorithm is certainly important, considering the importance of banknote evidence in forensic applications and the challenges involved in latent enhancement, we believe that developing a specific purpose fingerprint enhancement algorithm for latents on banknotes is both reasonable and necessary.

The idea behind the proposed latent enhancement algorithm is to detect local ridge orientation in the latent by using a clean banknote as a reference. To make the algorithm fully automatic, we proposed a coarse-to-fine registration algorithm to align the reference banknote with respect to the latent. With the orientation field available, the latent can be effectively enhanced using the Gabor filtering technique. The proposed algorithm was evaluated using 192 latents on RMB banknote of 1 yuan. The matching experiment including a background database of 27,000 fingerprints shows that the proposed algorithm significantly improved the rank-1 identification rate.

A major limitation of the current algorithm is the computational complexity, especially in the coarse-to-fine registration. We will try keypoint based registration methods in the future.

Acknowledgment

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