Slap fingerprint segmentation for live-scan devices and ten-print cards

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Abstract

Presented here is a highly accurate and computationally efficient algorithm suitable for slap fingerprint segmentation. The main advantages of this algorithm are as follows: 1) three-order cumulant is used to roughly segment the foreground; 2) frequency domain analysis is carried out in local areas to do binarization and fine segmentation; 3) cumulative sum analysis is applied to extract the knuckle lines; 4) two shape features of the ellipse are adapted to calculate the confidence of each fingertip candidate. Experimental results show that the algorithm has the characteristic of more robustness against noise and superior precision, not only for live-scan four finger slaps but also for ten-print-card five finger slaps.

1. Introduction

Currently the Department of State (DOS) and Department of Homeland Security (DHS) US-VISIT program are migrating from two-finger capture to ten-print capture[3]. The additional biometric information will be used to check fingerprints against important databases, such as the Federal Bureau of Investigation’s (FBI) Integrated Automated Fingerprint Identification System (IAFIS). Traditional ten-print cards include the rolled impressions of the ten fingers and two to four slap impressions. For example, Figure 1 shows a typical left-four-finger slap from a live-scan device and Figure 2 shows a typical right-five-finger slap from a ten-print card. Slap fingerprints are noted for the speed at which they can be collected and processed[3]. However, fingerprint images can not be matched against an image of a group of fingers. For this reason, the slap fingerprints are necessary to be quickly and accurately segmented into individual fingerprint images. The whole process where the slap image is divided up into individual images is called slap fingerprint segmentation[2]. It consists of two steps: 1) finding the segmentation positions; 2) using them to separate the image into individual images. The ability to evaluate and improve segmentation technology on slap fingerprints will have a significant impact on those agencies, such as DOS and DHS[3].

In [7], the slap image was segmented into disconnected regions using edge detection and a convex hull calculation on the different components, and then the components which were expected to form a hand geometry were identified and selected. In [5], a combination of two-staged mean shift and ellipse-fitting algorithms as well as an elaborate subsequence set of rules was used to segment the single fingertip images. In 2004, the National Institute of Standards and Technologies (NIST) conducted a fingerprint slap segmentation study (SlapSeg04) to assess the fingerprint segmentation technology[2]. In order to reassess the state-of-the-art of segmentation algorithms, NIST organized
the SlapSegII evaluation in 2008. The most significant differences between SlapSegII and SlapSeg04 are the metrics used to determine successful segmentation and the availability of 3-inch slap fingerprint data[3]. Compared with SlapSeg04, the results of SlapSegII are more encouraging. However, slap segmentation is still difficult and challenging mainly because of the following scenarios: 1) not clearly separated in an image; 2) background noise; 3) the halo effect; 4) rotation.

The aim of the algorithm proposed in this paper is to develop such an algorithm with more robustness and superior precision. The main steps are as follows: 1) coarse-to-fine separation of the foreground from the background; 2) extraction of knuckle lines; 3) coarse-to-fine estimation of the principal direction of the total slap; 4) detection of the fingerprint segmentation positions. In the following sections, the proposed algorithm will be presented in detail. Section 3 shows our experimental results tested on the live-scan four-finger-slap dataset and the ten-print-card five-finger-slap dataset. Finally, Section 4 gives the conclusion.

Figure 1. Typical slap fingerprint image

Figure 2. Typical slap fingerprint image from scanned inked cards

2. Algorithm

As shown in Figure 3, the main steps of our algorithm are as follows:

(1) Preprocessing: the original slap image is resampled to 1/16 of its original size and formatted to be 8-bit gray scale and reversed. And then, the slap is normalized so that it has the prespecified mean and variance as described in [6].

(2) Coarse segmentation: the preprocessed image is segmented using three-order cumulant[9]. For each central pixel \((x, y)\) in its corresponding \(8 \times 8\) local block, the three-order cumulant \(\Gamma(x, y)\) is calculated as follows: \(\Gamma(x, y) = E(x, y) \times D(x, y)\), where \(E(x, y)\) is the mean value and \(D(x, y)\) is the corresponding variance. The pixel \((x, y)\) is considered as a background pixel if \(\Gamma(x, y)\) is smaller than a given threshold \(T_0\).

(3) Binarization: the image is binarized using frequency domain analysis, similar to the algorithm proposed in [1]. However the local window is shifted pixel-by-pixel throughout the image in [1], the step is 4-pixel in our algorithm for accelerating the processing. After binarization, median filtering as the postprocessing is performed to reduce noise.

(4) Fine segmentation: the local ridge frequency \(\Upsilon(x, y)\) of each block is estimated based on a search of the maxima in the Fourier magnitude spectrum \(\Psi(x, y)\)[8]. A block is considered as a background, if its \(\Upsilon(x, y)\) is smaller than a given threshold \(T_1\).
(5) Region merging: if the distance between two isolated foreground regions is smaller than a given threshold \( T_2 \), these two foreground regions are merged.

(6) Local orientation evaluation: the ellipse-fitting algorithm proposed in [5] is used to determine the orientation \( \Theta_i \) of each foreground region \( F_i \).

(7) Knuckle lines extraction: cumulative sum analysis is used to extract the knuckle lines. Suppose that \( \Phi(x, y) \) denotes the local ridge orientation of the block centered at \((x, y)\) and \((x_j, y_j)\) is one pixel of the semimajor axis of \( F_i \), and \( \Omega_j \) is the line which is parallel to the semiminor axis of \( F_i \) and through the point \((x_j, y_j)\). The cumulative sum \( C(x_j, y_j, \Theta_i) \) is defined as follows:

\[
C(x_j, y_j, \Theta_i) = \sum_{(x, y) \in \Omega_j \subseteq F_i} (\Psi(x, y) \times \zeta(\Theta_i + \frac{\pi}{2}, \Phi(x, y))),
\]

where \( \zeta(\bullet, \bullet) \) is a function to calculate the difference between two angles. The smaller \( C(x_j, y_j, \Theta_i) \), the more possible the corresponding knuckle line. The line \( \Omega_k \) with the minimum \( C(x_j, y_j, \Theta_i) \) is considered as the knuckle line of \( F_i \):

\[
\Omega_k = \arg \min_{j \in [1, L_i]} C(x_j, y_j, \Theta_i),
\]

where \( L_i \) is the length of the semimajor axis of \( F_i \). Those foreground regions below the knuckle lines are removed.

(8) Coarse principal direction estimation: weighted averaging algorithm is used to estimate the principal direction \( \Theta \) of the total slap as follows:

\[
\Theta = \frac{1}{\sum_{1 \leq i \leq M} (A_i \times \theta_i)} / \sum_{1 \leq i \leq M} A_i,
\]

where \( A_i \) is the area of the foreground region \( F_i \) and \( M \) is the number of the left foreground regions.

(9) Fingertip region validation: the centre of each foreground region is projected along the direction, which is perpendicular to \( \Theta \). If the distance between two projection points is smaller than a given threshold \( T_3 \), the topper one is chosen as the fingertip region while the bottom one is removed.

(10) Confidence evaluation: the confidence \( \Xi_i \) of each fingertip candidate is defined using the following two shape features: 1) the ratio \( R_i \) between the semimajor axis and the semiminor axis; 2) the area \( A_i \). The bigger \( R_i \), the higher \( \Xi_i \); the bigger \( A_i \), the higher \( \Xi_i \). The confidence \( \Xi_i(R_i, A_i) \) is calculated as follows:

\[
\Xi_i(R_i, A_i) = \frac{(R_i * A_i)}{(R_T * A_T)},
\]

where \( R_T \) and \( A_T \) are two given thresholds. If \( R_i > R_T \), \( R_i \) is set to be equal to \( R_T \); similarly \( A_i \) is equal to \( A_T \), when \( A_i > A_T \).

(11) Fine principal direction estimation: when \( \Xi_i \) is smaller than a given threshold \( T_3 \), the evaluated principal direction \( \Theta \) is optimized using the minimum variation. For each different candidate principal direction \( \Theta_j \in [\Theta - T_\Theta, \Theta + T_\Theta] \), the centre of each fingertip is projected along \( \Theta_j \)'s vertical direction, where \( T_\Theta \) is a given threshold. The distance \( D_{j,k} \) between two neighbor projection points is calculated. The distance variation \( V_j \) is defined as follows:

\[
V_j = \sum_{k=1}^{K-1} (D_{j,k} - D_{j,k+1})^2,
\]

where \( K \) is the number of fingertips. The direction with the minimum variation is considered as the optimal principal direction \( D_{opt} \):

\[
D_{opt} = \arg \min_{j \in [1, K \times 2 \times T_\Theta]} V_j.
\]

(12) Fingertip location: the mathematical morphology is used to remove the spurs and holes[4]; According to the estimated principal direction (named the angle of rotation in [3]), the \( x \) and \( y \) coordinates for all four corners of the segmentation box for each candidate fingertip is calculated.

3. Experimental Results

3.1 Evaluation Data

Two datasets named LIVE-ZJUT and SCAN-ZJUT were created. Each dataset contained 1000 left hand slaps and 1000 right hand slaps. All of them were with both right and left slap images from the same person. Those slap images in LIVE-ZJUT were captured by the scanner (CROSSMATCH L SCAN Guardian), and each slap image was with 1500 \( \times \) 1600 and 500dpi as shown in Figure 1. Those slap images in SCAN-ZJUT was provided by the Criminal Investigation Corps of Zhejiang Provincial Public Security Department of China. Figure 2 shows a typical example with 2050 \( \times \) 1600 and 24-bit, which is cut from a scanned ten-print card.

3.2 Examples

This section presents segmentation examples generated by our proposed algorithm. The results shown in Figure 4 and Figure 5 are very satisfying.

3.3 Dataset Ground Truth

The ground truth data is based on the NIST fingerprint segmentation algorithm(NFSEG) and humans examine every slap image and hand correct all errors producing the ground truth segmentation coordinates[3].
The algorithm (Algorithm-A) in [5] and our proposed algorithm (Algorithm-B) were compared on the LIVE-ZJUT and SCAN-ZJUT datasets. Here correct segmentation means that the evaluated segmentation coordinates are within the tolerance limits specified in [3]. By count the number (denoted as ECount) of the falsely segmented slaps, the successful segmentation rates (denoted as SRate) were calculated simultaneously, as shown in Table 1. It has shown that the performance of Algorithm-B was much better than that of the Algorithm-A, especially for the SCAN-ZJUT dataset.

4 Conclusion

The proposed slap fingerprint segmentation algorithm has shown to be highly accurate not only for live-scan four finger slaps but also for inked-card five finger slaps. Experimental results indicate that this algorithm performs favorably. Our future work includes speeding-up our algorithm and making the algorithm more reliable to segment those challenged slap images.

Acknowledgement

This work has been founded by the Zhejiang Association for Science and Technology of China. The scanned inked cards used in our experiments were provided by the Criminal Investigation Corps of Zhejiang Provincial Public Security Department of China.

References