A Coarse-fine Fingerprint Scaling Method

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Abstract

Fingerprint scaling is an important issue for fingerprints from different capture sensors. A good scale would process the resolution difference and somewhat the distortion of fingerprints. In this paper, we develop a coarse-fine method to estimate the optimal scale between the input and template fingerprints. The global scale is coarsely calculated based on the ridge distance map and finally determined by the histogram of local refined scale between all the matchable minutiae pairs. Experimental results demonstrate that our algorithm effectively improves the matching accuracy of the fingerprints from multi-type capture sensors.

1. Introduction

Fingerprint is one of the most used biometrics. Recently great improvement has been achieved in the fingerprint sensing technology and automatic recognition algorithms. The development of sensor technology allows us to acquire on-line fingerprints with various types of sensors, while the difference among multi-type sensors will significantly affect the characteristics of the raw data, the extracted features and the similarity score generated by matching algorithm.

We define the matching of fingerprints from multi-type sensors as ”cross-matching” in contrast to ”regular matching”. The transformation in the cross-matching includes translation, rotation, scale and non-linear distortion. Since the typical fingerprint scanners are supposed to have the same horizontal and vertical resolution, scale can be defined as the global variable by which the template fingerprint should be zoomed to accord with the input one at the utmost. The value of scale is mainly determined by the systematic sensor resolution which is invariant for two appointed types of sensors, but it is otherwise effected by non-linear distortion during fingerprint capture. Selecting the optimal scale for each pair of compared fingerprints may somewhat improve the ability of matchers to tolerate non-linear distortion.

Jang et.al [5] improved the interoperability of fingerprint recognition using resolution compensation based on sensor evaluation. However, it needs to manually measure the initial resolution in two directions and is only available for the press sensors. He et. al [3] proposed a maximum-likelihood estimation method to model the deformation parameters between two fingerprints. The variants of scale, as two dimensions in the possible deformation parameter space, are optimally determined by maximizing the global similarity calculated based on the minutiae features. Tan and Bhanu [11] proposed an optimization-based matching algorithm by genetic algorithms. The optimal scale was selected by the genetic algorithm from the transformation space with the chromosome representation. The two approaches above introduce the scale parameter into the transformation and can be employed in the cross-matching of fingerprints, but they construct the transformation space combining scale, rotating and translation, so the scale, as one of the dimensions, must be estimated dependant on the other parameters, which made the performance of estimation rely heavily on the effectivity of searching method.

In this paper, we focuses on scale optimization for fingerprints from multi-type sensors to improve the performance of fingerprint cross-matching. After preprocessing, a coarse-fine method is used to estimate the scale between the input and template fingerprints before fingerprint registration, where the scale is estimated separately from rotation and translation parameters. Experiments are conducted to testify the effectivity of our scale method.

The rest of the paper is organized as follows: Section 2 describes the feature extraction for scale. Section 3 introduces the coarse-fine scale method. The experimental results are displayed in section 4 and Section 5 summarizes our researches.

2. Feature Extraction

The main features we used for scale are minutiae and ridge distance. The later one will be calculated in Section 3.1 with the coarse scale estimation. The method we used to extract the former and the preprocessing steps will be describes in this Section.

The original fingerprint images is first segmented from the background by the following processes: the image is divided into many blocks of size $n * n$, and three statistic features, the mean value, the variance of the gray levels and the clusters degree [1] were calculated for each block. Using a linear classifier, we can decide whether a certain block belongs to the background or the valid region.

Then We adopt global orientation model to modify the orientation feature in the low-quality fingerprints. First the gradient-based approach [4] is used to compute the coarse orientation. Then we measure the reliability of orientation at each point using the normalized coherence of the gradient within the neighborhood area. The blurred region is detected composing of those points with a lower reliability value than a certain threshold. The orientation in these regions is considered incorrectly computed, which will be corrected by the 2D Fourier-based orientation model [14].

The Gabor filter is applied to enhance the fingerprint with the advantages of its robust ridge enhancement and efficient noise removing. Then the ridge-line skeleton is obtained by thinning the binary ridges. The valley skeleton is also obtained by the same way. Finally minutiae are extracted, from both skeletons, using the the crossing number [9].

3. Scale Adjusting Based on the Coarse-fine Method

In this section, a coarse-fine method is proposed to complete the scale adjusting between the input and template fingerprints. The initial scale is estimated based on the modeled ridge distance map. The local scale is respectively refined in the neighborhood range centered around the initial scale to maximize the similarity of the compared minutiae. In the refining process we represent the minutiae feature with the adjacent minutiae structure, which is proved robust to distortion. Finally the global scale is determined by the histogram of the local scale between all the possibly matchable minutiae pairs.

3.1. Coarse Scale Estimation Based on Ridge Distance Map

The ridge distance is defined as the length of segment connecting the centers of two adjacent and parallel ridges along the perpendicular direction to the ridges. It is one of the stable features of fingerprint, which can effectively characterize the difference of scales in the multi-type fingerprints. The researches on the ridge distance calculation mainly contain two ways [7]: one is the spectral approach and the other is the spatial approach. The former one is robust to noise but needs largish computation cost, so in our method the coarse global ridge distance map is obtained by the later one due to its effectiveness. However, the ridge distance usually varies sharply around the minutiae and singulary points. Considering the continuity of ridge distance, it is reasonable to utilize the polynomial approximation to smooth away the acuity over the map [13]. The modeled map is proved more robust to noise and distortion than the original one. Based on the experimental results, we choose the 4-order polynomial model as a tradeoff in balancing the computational cost and estimative accuracy. Then we can calculate the global ridge distance of the fingerprints as the average of all the values in the modeled map.

Here this ridge distance is utilized to estimate the initialized scale between the input and template fingerprints. We coarsely determine the initial scale sl_0 as the quotient of the global ridge distance of two compared fingerprints. However, sl_0 is proved not appropriate to be directly applied to the recognition scheme because of the distortion and inevitable deviation in the ridge distance estimation. According to our experimental results, the variation of optimal scale generally locates in the range $sl = \rho * sl_0$, where $\rho \in [0.9, 1.1]$.

3.2. Local Scale Refining Based on Adjacent Minutiae Structure

In this section, the local scale is refined based on maximizing the similarity between a pair of compared minutiae. The minutiae set denoted by $\{M^k = (x_m^k, y_m^k, \theta_m^k) | 1 \leq k \leq K\}$ are extracted from the thinned fingerprints with the conventional method, where K is the number of minutiae; (x_m^k, y_m^k) and $\theta_m^k \in [0, 2\pi)$ are respectively the location and direction for the k^{th} minutia M^k. We extract the adjacent minutiae structure to represent the distribution of adjacent minutiae circled around a minutia with a preset radius, which is proved effective on the matching of large-distorted fingerprints [2]. The features are composed of the location and direction information relative to the centered minutia, so they are invariant to the rotation and translation of the fingerprint.

The local minutiae structure of the i^{th} minutia is expressed as $M_i = \{m_{i,j} | j = 1...n_i\}$, where n_i is the number of these minutia around m_i within the R_p radius (R_p is empirically set 5 to 7 times as large as the global ridge distance with different databases). As displayed in Fig. 1, $m_{i,j}$ is utilized to describe the branch between m_i and its j^{th} adjacent minutia m_j^i:

$$m_{i,j} = (L_{i,j}, N_{i,j}, \beta_{i,j}^1, \beta_{i,j}^2) \quad (1)$$

where $L_{i,j}$ denotes the length of branch, which is calculated

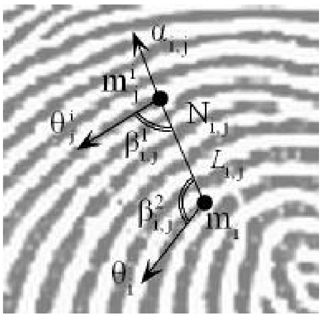

Figure 1. The relationship between m_i and its j^{th} adjacent minutia m^i_j.

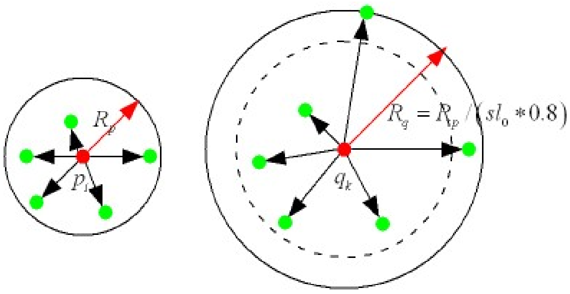

Figure 2. Two adjacent structures for a pair of corresponding minutiae p_i and q_k from the input and template fingerprints.

as the Euclidean distance between m_i and m^i_j; $N_{i,j}$ records the number of ridges across the branch, which is counted during the minutiae detection; θ_i, θ^i_j are respectively their direction; $\alpha_{i,j}$ is the direction of the connecting line from m_i to m^i_j; $\beta^1_{i,j} = \beta(\theta_i, \alpha_{i,j})$ and $\beta^2_{i,j} = \beta(\theta^i_j, \alpha_{j,i})$; $\beta(\alpha_1, \alpha_2)$ is called directional distance function defined in the Eq. 2. Among these parameters, $L_{i,j}$ is in proportion to the scale of fingerprint, whereas the others are invariant.

$$\beta(\alpha_1, \alpha_2) = \begin{cases} \alpha_1 - \alpha_2 & \text{if } |\alpha_1 - \alpha_2| \le \pi \\ \alpha_1 - \alpha_2 - 2\pi & \text{if } (\alpha_1 - \alpha_2) > \pi \\ \alpha_1 - \alpha_2 + 2\pi & \text{else} \end{cases} \quad (2)$$

Let $Mp_i = \{mp_{i,j} | j = 1...np_i\}$ and $Mq_k = \{mq_{k,l} | l = 1...nq_k\}$ respectively denote the minutiae structures of two minutiae p_i and q_k from the input and template fingerprints. Since the scale sl is assumed to vary in the range $sl_0 * \rho$ and $\rho \in [0.9, 1.1]$, we adopt the radius $R_q = R_p/(sl_0 * 0.8)$ to ensure the input structure includes all the requisite minutiae. However, it is still possible to miss some marginal minutiae due to the local distortion. Fig. 2 displays two structures for a pair of corresponding minutiae p_i and q_k from the input and template fingerprints.

For each pair of branches $mp_{i,j}$ and $mq_{k,l}$ from two structures, we calculate their difference vector composed of four parameters as:

$$\begin{aligned}(L_d, N_d, \beta^1_d, \beta^2_d) = (&|Lp_{i,j} - Lq_{k,l} * sl|, |Np_{i,j} - Nq_{k,l}|, \\ &|\beta(\beta p^1_{i,j}, \beta q^1_{k,l})|, |\beta(\beta p^2_{i,j}, \beta q^2_{k,l})|)\end{aligned} \quad (3)$$

Since $N_{i,j}$ is in proportion to the length of branch but independent of the scale, it is used to preset the boundary for the matched pair of branches instead of L_d. Once the difference vector satisfies the following conditions: $N_d < N_{thr}$, $\beta^1_d < \beta_{thr}$ and $\beta^2_d < \beta_{thr}$, the pair of branches is considered matchable. If the distance of branch is small, a little displacement will cause a large disturbance to the directional angle. If the distance is large, a little rotating will bring out a large change of the minutia position. The method of changeable tolerance box [8] is used to determine the threshold N_{thr} and β_{thr}.

For each branch in Mp_i we select its corresponding branch in Mq_k according to the rule of minimum difference vector. If the ratio n_{match}/np_i exceeds a certain threshold, the compared structures are considered matched. Their similarity is estimated based on the average difference vector $(\bar{L_d}, \bar{\beta^1_d}, \bar{\beta^2_d})$ for n_{match} pairs of matched branches:

$$S(p, q) = exp\{-(\frac{1}{\lambda_1} * \bar{L_d} + \frac{1}{\lambda_2} * \bar{\beta^1_d} + \frac{1}{\lambda_2} * \bar{\beta^2_d})\} \quad (4)$$

where λ_1 is set twice as large as the global ridge distance of the input fingerprint, and $\lambda_2 = \pi/10$ in our experiments. λ_1 and λ_2 are determined through two steps: We select some fingerprint pairs in genuine and imposter matching, manually extract two sets of genuine and imposter matched structures and obtain their difference vectors for training. 1) The ratio of two parameters is determined to optimize the classification for those difference vectors. 2) Since the matching score is calculated based on the similarity of matched structures, we finally select the value to optimally distinguish genuine matching from imposter one.

In the expression of $S(p, q)$, only the average length difference $\bar{L_d}$ involves the scale variant sl in a piece-wise linear form. In the Sec. 3.1, we have estimated the initial scale sl_0 between the pair of minutiae based on the ridge density map. We then convert the range of $\rho \in [0.9, 1.1]$ into a discrete space with the resolution of 0.005. The optimal local scale is selected from this scope by the linear optimization method to minimize the value of $\bar{L_d}$.

3.3. Global Scale Estimation by Histogram

Two sets of minutiae from the input and template fingerprints are denoted as $\{p_i = (x^p_i, y^p_i, \theta^p_i, Rp_i, Mp_i) | i = 1...n_p\}$ and $\{q_k = (x^q_k, y^q_k, \theta^q_k, Rq_k, Mq_k) | k = 1...n_q\}$. For each pair of minutiae p_i and q_k, we get the optimal local scale $sl_{i,k}$ and their similarity $S(p_i, q_k)$. If $S(p_i, q_k) > s_{thr}$, the corresponding scale is taken into account in the global scale estimation (s_{thr} is empirically set as 0.3). The histogram function $H(sl)$ is used to describe the distribution of the local scale for all pairs of minutiae. Due to the mistake during estimation, there may exist some burrs in the chart of histogram, so a low-pass filter is utilized to remove the burrs and smooth the histogram. If the matched fingerprints come from the same finger, it is reasonable that the value of $sl_{i,k}$ should concentrate around the correct global scale sl_g. Fig. 3 illustrates two fingerprints from the same finger and their histogram charts before and after smoothing. Theoretically the global scale sl_g is chosen according to the condition $H(sl_g) = max(H(sl))$. However, practically sl_g is affected by the noise and distortion so it may have a certain deviation. The global scale is modified as the weighted sum of $sl_{i,k}$ in the neighborhood $U = [sl_m - \sigma_1, sl_m + \sigma_2]$, where $H(sl_m) = max(H(sl_{i,k}))$, σ_1 and σ_2 is the largest value that assures $H(sl)/H(sl_m) \geq 2/3$.

$$sl_g = \frac{\sum_{sl \in U} sl * H(sl)}{\sum_{sl \in U} H(sl)} \tag{5}$$

The variant σ denotes the convergence of the scale and has the competence to distinguish the genuine match from imposter one. If the interval U is far greater than a preconcerted width, the distribution of scale is considered disorder and the compared fingerprints is regarded unmatched.

3.4. Similarity Calculation after Scale

The Scale parameter has been globally estimated in Section 3.3. We update the Similarity $S(p_i, q_k)$ for each pairs of minutiae with the global scale sl_g. If two minutiae have large similarity, we incline to consider them as corresponding ones. However, similarity is not distinguishing enough to definitely identify the corresponding pair since there may be several similar candidates for one input minutia. We therefore estimate the possibility of correspondence between a minutiae pair (p_i, q_k) based on not only their similarity but also their distinctness from other minutiae in comparison respectively [12].

$$P(p_i, q_k) = \frac{S^2(p_i, q_k)}{\sum_n S(p_i, q_n) + \sum_m S(p_m, q_k) - S(p_i, q_k)} \tag{6}$$

We start registration from the minutiae pair of the largest corresponding possibility, which is marked as (p_o, q_o). The parameters of translation and rotation are calculated as the average difference of location and orientation for all the minutiae pairs in the adjacent structures of (p_o, q_o).

After registration, the global similarity of the two compared fingerprints is calculated as the mean of the similarity $S(p_i, q_k)$ of all the corresponding minutiae pairs.

4. Experimental Results

In order to validate the performance of our algorithms, we conduct series of experiments on FingerPass

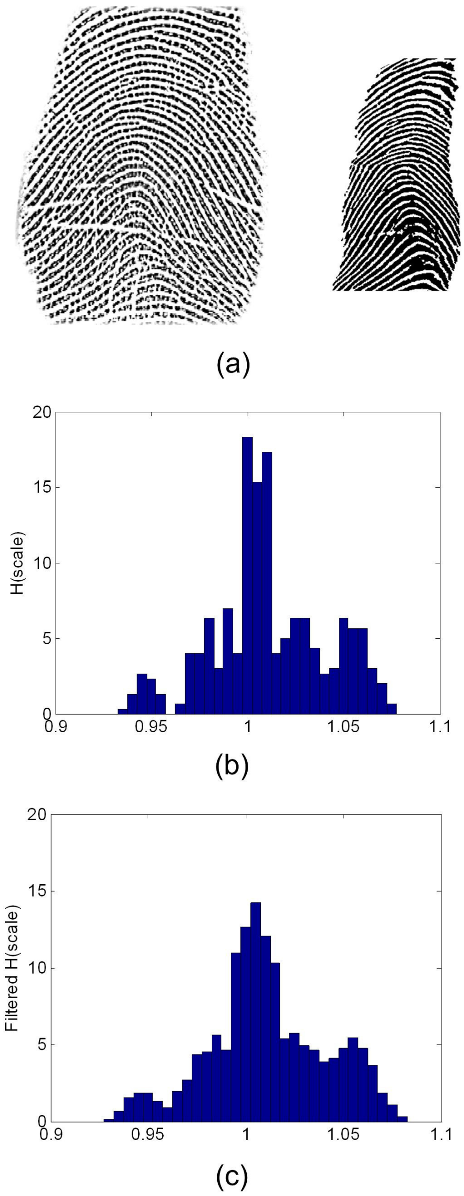

Figure 3. (a)Two fingerprints from the same finger with press sensor and sweep sensor; (b)The histogram of scale: H(scale); (c)The filtered histogram of scale;

database [6]. Four sub-databases are chosen, which are constructed with URU4000B optical press sensor, UPEK TCRU2C capacitive press sensor, Authentec AES2501 sweep sensor and and Symwave SW6888 thermal sweep sensor, separately. Each sub-database contains 720*12 impressions (720 fingers, 12 impressions per finger).

Tab. 1 describes the characteristics of these four sub-databases, where we can see that the resolution of URU4000B sensor is 700dpi, different from the other three sensors (about 500dpi). Fig. 4 gives an example including

Table 1. Characteristics of the chosen sub-databases.

	Capture Sensor	Image Size	DPI
DB1	URU 4000B	500*550	700
DB2	UPEK TCRU2C	208*288	508
DB3	Authentec AES2501	Unfixed	500
DB4	Symwave SW6888	288*384	500

Figure 4. Four impressions from the same finger in the chosen sub-databases.

four impressions from the same finger. Fingerprints from URU sensor have obvious fine pore features on their ridges due to the higher resolution. So we conduct three sets of cross-matching experiments between URU4000B and other three sensors.

Two other scale adjusting approaches, which respectively estimate the scale based on the known DPI of sensors and density, are proposed for comparison. The DPI-based method directly calculates the scale parameter as the quotient of the known resolution of two compared sensors (e.g. scale between URU and UPEK is 700dpi/508dpi). The density-based method directly utilizes the coarse scale for each cross-matching as calculated in Sec. 3.1 without refining stage.

The sequence of the compared fingerprints in cross-matching is arranged as following: In genuine match each impression is matched against all the impressions of the same finger to compute the False Non-Match Rate(FNMR); In imposter match the first impression of each finger is matched against the first sample of the remaining fingers to compute the False Match Rate(FMR). To sum up, a total of $103,680$ $(720 * 12 * 12)$ genuine matching and $258,840$ (C_{720}^2) imposter matching are conducted for each cross-matching.

Tab. 2 illustrate the performance of the proposed scale estimation methods and those of the two compared ones. The regular matching results of the four chosen sub-databases are reported as well. For the reason that fingerprints from the same sensors has the same resolution, there is no need to do the scaling in regular matching. And only 47520 $(720 * C_{12}^2)$ genuine matching is done for regular matching. All experiments are conducted on PC Intel Core i5 650 @ 3.20 GHZ.

Based on the experimental results, the following conclusions can be drawn out:

1). EERs of regular matching are far more satisfying than those of cross-matching. Furthermore, EERs in cross-matching between the same kind of sensors (URU vs. UPEK) obviously outperforms that between different kinds of sensors(URU vs. AES, URU vs. SW). The comparison confirms the matching performance is greatly deteriorated by non-linear distortion and different distortion patterns.

2). The DPI-based method is effective to estimate the global scale resulted by the systematic difference of sensors. The density-based method has the worst performance because the feature of ridge distance relies on the quality of fingerprints and is variable due to the different distortion during acquisition. Different from two methods above which predetermine the scale parameter before matching process, our method utilizes the coarse-fine method to estimate the value of global scale during the cross-matching processing. The comparison confirms our method achieves better performance.

3). There are two ways in which the scale adjusting benefits the cross-matching, especially for those fingerprints in different acquisition modes. The global optimal scale makes it more probable to better select the initial pair of corresponding minutiae and hence effect the results of feature registration. Scale adjusting also obtains more candidate pairs of corresponding minutiae between the overlapped areas of two distorted fingerprints so it can decrease FNMR of matching.

5. Conclusion

In this paper, a novel coarse-fine scale adjusting algorithm is developed for the fingerprints from multi-type sensors. The experimental results demonstrate that our algorithm achieves good performance in fingerprint cross-matching.

In future, we will do the researches on automatic scaling for fingerprints from multi-type sensors and try to combine

Table 2. The performance of regular matching and cross-matching of proposed algorithms and comparison algorithms on three FingerPass databases.

	Scale Method	EER(%)	FMR100	FMR1000	ZeroFMR(%)	avgTime(s)
URU	none	0.058	0.032	0.045	0.936	0.118
UPEK	none	0.103	0.065	0.132	1.374	0.091
AES	none	0.087	0.056	0.079	1.082	0.106
SW	none	0.126	0.087	0.155	2.172	0.102
URU	DPI	0.532	0.357	0.892	2.384	0.159
vs.	DENSITY	0.574	0.396	0.994	2.120	0.176
UPEK	Proposed	0.489	0.288	1.016	2.214	0.208
URU	DPI	2.688	6.547	12.380	22.631	0.142
vs.	DENSITY	3.714	6.632	15.504	23.645	0.158
AES	Proposed	2.445	5.913	10.451	18.626	0.196
URU	DPI	2.903	4.251	6.897	10.460	0.135
vs.	DENSITY	3.942	7.020	11.120	18.582	0.162
SW	Proposed	2.648	3.972	5.216	9.376	0.190

the scale method in this paper with some distorted models.

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