Robust Fingerprint Identification

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ABSTRACT

Due to the complex distortions involved in two impressions of the same finger, fingerprint identification is still a challenging problem for person authentication. In this paper, we propose a fingerprint identification approach based on the triplets of minutiae. The features that we use to find the potential corresponding triangles include angles, triangle orientation, triangle direction, maximum side, minutiae density and ridge counts. False corresponding triangles are eliminated by applying constraints to the transformation between two potential corresponding triangles. The experimental results on National Institute of Standards and Technology special fingerprint database 4, *NIST-4*, show that, as compared to the linear search, the proposed approach provides a reduction by a factor of 200 for the number of the hypotheses that need to be considered and it can achieve good performance even when a large portion of fingerprints in the database are of poor quality.

1. INTRODUCTION

Fingerprints have been used for person authentication for a long time. Now, they are not only used by police for law enforcement, but also in commercial applications. In terms of applications, there are two kinds of systems, which use fingerprints for the personal identity: verification and identification. In verification, the input is a query fingerprint and an identity (ID), the system verifies whether the ID is consistent with the fingerprint. The output of a verification system is an answer of yes or no. Identification system is more challenging since the input is only a query fingerprint and the system should answer the question: are there any fingerprints in the database, which resemble the query fingerprint? In this paper, we are dealing with the identification problem.

There are three kinds of approaches to solve the fingerprint identification problem: 1) repeat the verification for each fingerprint in the database and select the best match; 2) fingerprint classification followed by verification; and 3) fingerprint indexing followed by verification. Figure 1 shows the block diagrams of these approaches. The first approach is based on a verification technique. Recent techniques for fingerprint verification can be found in [4,6,7]. However, if the size of the database is large, these approaches, based on linear search, will be impractical for real-world applications. The traditional classification techniques used in the fingerprint recognition attempt to classify fingerprints into five classes: Right Loop (R), Left Loop (L), Whorl (W), Arch (A), and Tented Arch (T). Classification techniques based on different features and algorithms can be found in [2,5,9]. However, because the number of principal classes is small and the fingerprints are unevenly distributed (31.7%, 33.8%, 27.9%, 3.7%, and 2.9% for classes R, L, W, A and T, respectively), the classification approach can not narrow down the search enough in the database for efficient identification of a fingerprint. The goal of the third approach is to significantly reduce the number of candidate hypotheses to be considered by the verification algorithm, which selects the best hypothesis. A prominent approach for fingerprint identification is by Germain et al. [3], which integrates the indexing and verification in their approach (Figure 1.3(a)). They use the triplets of minutiae in their identification procedure. The features they use are: the length of each side, the ridge count between each pair of vertices, and the angles that the ridges make with respect to the X-axis of the reference frame. The problems with their approach are: a) the length changes are not insignificant under distortions; b) the angles change greatly with different quality images of the same finger; and c) uncertainty of minutiae locations is not modeled explicitly. As a result, large size bins have to be used to handle distortions, which increases the probability of collisions and degrades the performance.

Our approach presented in this paper follows Germain et al. [3] in that we also use the triplets of minutiae. However, the indexing and verification in our approach are separated (Figure 1.3(b)). Firstly, we apply indexing techniques to find top N (N=10 in our experiments) hypotheses, and then apply verification technique to verify hypotheses. Also, most features that we use are quite different from theirs. The features that we use are: triangle's angles, orientation, direction, maximum side, minutiae density and ridge counts. And we use the constraints of the transformation to eliminate the false corresponding triangles. There are two processing steps in our approach. During the offline processing step, model fingerprints are processed to construct the model database. During the online processing step, features of the query fingerprint based on the triplets of minutiae are used to find the potential corresponding triangles. Then, top 10 hypotheses are generated according to the number of potential

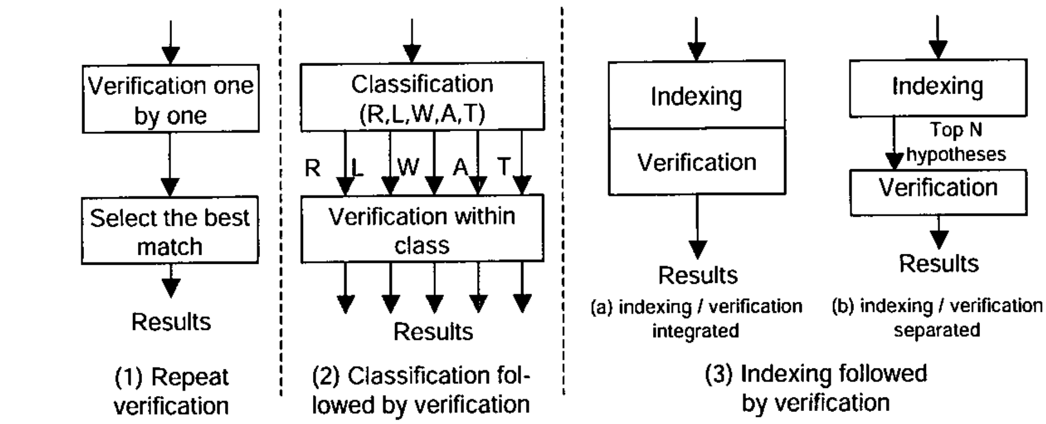

Figure 1. Block diagrams of three kinds of approaches to solve the identification problem.

corresponding triangles. These hypotheses are input to the verification system. The transformation between each pair of potential corresponding triangles is estimated using Mean Square Error (*MSE*). Finally, the constraints of the transformation are applied to eliminate the false corresponding triangles. The identification score is computed based on the number of corresponding triangles. The performance of our approach on the *NIST-4* database, which has a large portion of fingerprints of poor quality, shows that our approach is promising.

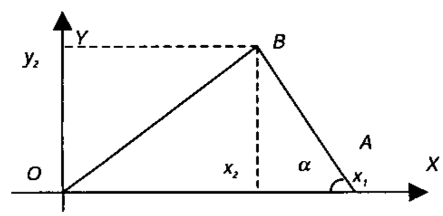

Figure 2. Illustration of variables.

2. TECHNICAL APPROACH

Figure 2 shows a triangle. Without loss of generality, we assume that one vertex, O, of the triangle is $(0, 0)$, and it does not change under distortions. The analysis of angle α shows that 1) the minimum and the median angles α_{min} and α_{med} in a triangle are more robust than the maximum angle α_{max} under distortions; 2) $2°$ can accommodate the uncertainty of most distortions and keep the size of the search space as small as possible. Details of the analysis can be found in [1].

2.1. Indexing

During the offline processing step, the features of each model fingerprint are computed and used to construct the indexing space $H(\alpha_{min}, \alpha_{med}, \phi, \eta, \lambda, \chi, \xi)$. During the online processing step, we compute the features for the query fingerprint and use them to search the indexing space $H(\alpha_{min}, \alpha_{med}, \phi, \eta, \lambda, \chi, \xi)$. If the feature values of two triangles, which are from two different fingerprints, are within some error tolerance, then they are potential corresponding triangles. The output of indexing is the list of hypotheses for potential match between the query and model fingerprints, which are sorted in a descending order of the number of potential corresponding triangles. Only the top N hypotheses are input to the verification step.The features we use to find potential corresponding triangles are defined in the following:

- **Angles α_{min} and α_{med}:** Suppose α_i are three angles in the triangle, $i = 1, 2, 3$. Let $\alpha_{max} = max\{\alpha_i\}$, $\alpha_{min} = min\{\alpha_i\}$, $\alpha_{med} = 180° - \alpha_{max} - \alpha_{min}$, then the label of the triplets in this triangle is such that if the minutia is the vertex of angle α_{max}, we label this point as P_1; if the minutia is the vertex of angle α_{min}, we label it as P_2; the last minutia is labeled as P_3. We use α_{min} and α_{med} as two components of index.
- **Triangle Orientation ϕ:** Let $Z_i = x_i + jy_i$ be the complex number ($j = \sqrt{-1}$) corresponding to the coordinates (x_i, y_i) of point P_i, $i = 1,2,3$. Define $Z_{21} = Z_2 - Z_1$, $Z_{32} = Z_3 - Z_2$, and $Z_{13} = Z_1 - Z_3$. Let $\phi = sign(Z_{21} \times Z_{32})$, where *sign* is the signum function and $\times$ is the cross product of two complex numbers.
- **Triangle Direction η:** Search the minutia from top to bottom and left to right in the fingerprint, if the minutia is the start point of a ridge or valley, then $v = 1$, else $v = 0$. Let $\eta = 4v_1 + 2v_2 + v_3$, where v_i is the v value of point P_i, $i = 1,2,3$.
- **Maximum Side λ:** Let $\lambda = max\{L_i\}$, where $L_1 = |Z_{21}|$, $L_2 = |Z_{32}|$, and $L_3 = |Z_{13}|$.
- **Minutiae Density χ:** In a local area (32×32 pixels) centered at the minutiae P_i, if there exists n_χ minutiae, then minutiae density for P_i is $\chi_i = n_\chi$. Minutiae density χ is a vector consisting of all χ_i's.
- **Ridge Counts ξ:** Let ξ_1, ξ_2 and ξ_3 be the ridge counts of sides P_1P_2, P_2P_3 and P_3P_1, respectively, then ξ is a vector consisting of all ξ_i's.

2.2. Verification

Suppose the sets of minutiae in the model and the query fingerprints are $\{(t_{n,1}, t_{n,2})\}$ and $\{(q_{m,1}, q_{m,2})\}$ respectively, where $n = 1,2,3,\ldots N$, $m = 1,2,3,\ldots M$. The number of minutiae in the model and the query fingerprints are N and M, respectively. Let Δ_t and Δ_q be two potential corresponding triangles in the model and the query fingerprints, respectively. The coordinates of the vertices of Δ_t and Δ_q are $(x_{i,1}, x_{i,2})$ and $(y_{i,1}, y_{i,2})$, respectively, and $i = 1,2,3$. Suppose $X_i = [x_{i,1}, x_{i,2}]'$, $Y_i = [y_{i,1}, y_{i,2}]'$, and the transformation $Y_i = F(X_i)$ can be expressed as:

$$Y_i = \begin{bmatrix}1 & \delta h_x\\ \delta h_y & 1\end{bmatrix}\begin{bmatrix}1+\delta s_x & 0\\ 0 & 1+\delta s_y\end{bmatrix} R\cdot X_i + T \qquad (1)$$

where $(\delta h_x, \delta h_y)$ and $(1+\delta s_x, 1+\delta s_y)$ are the shear and scale parameters, $R = \begin{bmatrix}\cos\theta & -\sin\theta\\ \sin\theta & \cos\theta\end{bmatrix}$, θ is the angle of rotation between two fingerprints, and $T = [t_1, t_2]'$ is the vector of translation.

Since $\delta h_x \ll 1$, $\delta h_y \ll 1$, and $\delta s_x \approx \delta s_y$, we can simplify equation (1) to:

$$Y_i = s\cdot R\cdot X_i + T \qquad (2)$$

where s is the scaling factor.

We estimate the transformation parameters by minimizing error ε^2, which is the sum of the squared distances between the transformed model points and their corresponding query points. That is,

$$error = \underset{(\hat s, \hat R, \hat T)}{\arg\min}\ \{\varepsilon^2\} \qquad (3)$$

where, $\varepsilon^2 = \sum_{i=1}^{3}\left\|Y_i - (\hat s\cdot \hat R\cdot X_i + \hat T)\right\|^2$, and $\|V\|$ is the L_2 norm of vector V.

The solution of equation (3) is

$$\hat\theta = \arctan\left(\frac{B}{A}\right),\quad \hat s = \frac{\sum_{i=1}^{3}\{(X_i-\bar X)'\hat R'(Y_i-\bar Y)\}}{\sum_{i=1}^{3}\{(X_i-\bar X)'(Y_i-\bar Y)\}}$$

$$\hat T = \bar Y - \hat s\cdot \hat R\cdot \bar X \qquad (4)$$

where

$$A = \sum_{i=1}^{3}\{(\bar x_1 - x_{i,1})(y_{i,1}-\bar y_1) + (\bar x_2 - x_{i,2})(y_{i,2}-\bar y_2)\} \qquad (5)$$

$$B = \sum_{i=1}^{3}\{(\bar x_1 - x_{i,1})(y_{i,2}-\bar y_2) - (\bar x_2 - x_{i,2})(y_{i,1}-\bar y_1)\} \qquad (6)$$

$$\bar X = \begin{bmatrix}\bar x_1\\ \bar x_2\end{bmatrix} = \sum_{i=1}^{3} X_i,\quad \bar Y = \begin{bmatrix}\bar y_1\\ \bar y_2\end{bmatrix} = \sum_{i=1}^{3} Y_i \qquad (7)$$

$$\hat R = \begin{bmatrix}\cos\hat\theta & -\sin\hat\theta\\ \sin\hat\theta & \cos\hat\theta\end{bmatrix},\quad \hat T = \begin{bmatrix}\hat t_1\\ \hat t_2\end{bmatrix} \qquad (8)$$

If $\hat s$, $\hat\theta$, $\hat t_1$ and $\hat t_2$ are less than certain thresholds, then we take them as the parameters of the transformation between two potential corresponding triangles Δ_t and Δ_q. Otherwise, they are false correspondences. Based on the transformation $\hat F(\hat s, \hat\theta, \hat t_1, \hat t_2)$, $\forall j$, $j = 1,2,3,\ldots N$, we compute:

$$d = \underset{k}{\arg\min}\left\{\left\|\hat F\left(\begin{bmatrix}t_{j,1}\\ t_{j,2}\end{bmatrix}\right) - \begin{bmatrix}q_{k,1}\\ q_{k,2}\end{bmatrix}\right\|\right\} \qquad (9)$$

If d is less than a threshold T_d, then we define the points $[t_{j,1}, t_{j,2}]'$ and $[q_{k,1}, q_{k,2}]'$ are corresponding points. If the number of corresponding points based on $\hat F(\hat s, \hat\theta, \hat t_1, \hat t_2)$ is greater than a threshold T_n, then we define Δ_t and Δ_q as the *corresponding triangles* between the model and the query fingerprints.

The identification score is simply the number of corresponding triangles between the query and model fingerprints.

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Figure 3. Sample images in *NIST-4* database.

3. EXPERMENTAL RESULTS

The database we use is the *NIST* special fingerprint database 4 (*NIST-4*) [8]. Since the fingerprints in *NIST-4* are collected by an ink-based method, a large portion of the fingerprints are of poor quality and contain certain other objects, such as characters and handwritten lines. The size of the images is 480x512 pixels with a resolution of 500 *DPI*. *NIST-4* contains 2000 pairs of fingerprints. Each pair is a different impression of the same finger. A pair of sample fingerprints is shown in Figure 3. In our experiments, the first 2000 fingerprints are used to construct the model database, and the second 2000 fingerprints are used as the query fingerprints. So, we did 2000 queries to test the Genuine Acceptance Rate (*GAR*) and 2000x1999 queries to test the False Acceptance Rate (*FAR*).

The Receiver Operating Characteristic (*ROC*) curve is defined as the plot of *GAR* against *FAR*. Figure 4 shows the *ROC* curve of the proposed approach on *NIST-4*. We observe that without rejecting any fingerprints from *NIST-4* database, the *GAR* and *FAR* can reach 83.0% and 0.2%, respectively. As the threshold for identification score increases, the *FAR* decreases to 0.0011% while the *GAR* is 71.8%. To the best of our knowledge, this is the first paper, which shows the identification results, obtained automatically, on the entire *NIST-4* database.

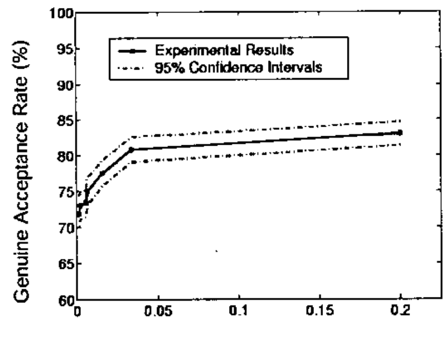

Figure 4. *ROC* curve of the experimental results.

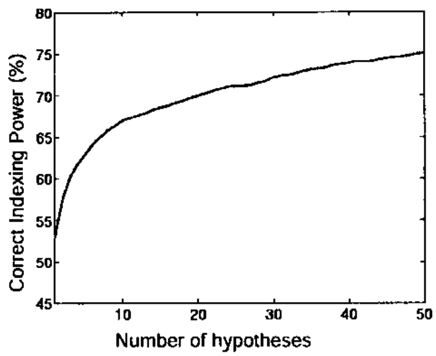

Figure 5. *CIP* of the approach on *NIST-4*.

Results on *NIST-4* are reported in [7]. However, the approach in [7] is for verification only and 6.0% data from *NIST-4* are rejected *manually* by the author because of bad quality. Without Dynamic Time Warping (*DTW*) for the detailed verification, the *FAR* is 10.0%, which is unacceptable, although the *GAR* is 85.0%. We can not compare the performance reported in [7] with *DTW* since the author has not used the entire database, and we do not know which of the fingerprints have been rejected manually. However, we implemented the approach described in [3], and compared our performance with it. Figure 5 shows the Correct Indexing Power (*CIP*) [1] of the approach in [3], where *CIP* is defined as the percentage of the correctly indexed images. If we take the top 1 hypothesis as the identification result, then *GAR* is 53.0% while *FAR* is greater than 10.0%. As compared to our results given in Figure 4, this performance on *NIST-4* is not good. One important reason is that the approach in [3] does not explicitly take into account the complex distortion, which is obviously presented in *NIST-4* database.

Closely examining the results, we find that: a) the low identification scores for most genuine queries are due to the poor quality of fingerprints. There are not enough overlapped areas where the feature extraction can extract enough corresponding minutiae; b) the nonzero identification scores for most imposter queries are due to the highly similar local structures in different fingerprints.

4. CONCLUSIONS

In this paper, we proposed a fingerprint identification approach based on the triplets of minutiae. The features we use to find potential corresponding triangles are based on the triplets of minutiae and can tolerate reasonable distortions, including translation, rotation, scale, shear, local perturbation, occlusion and clutter. Constraints for translation, rotation and scale are applied to the transformation parameters to eliminate the false corresponding triangles. The number of corresponding triangles provides a good local method to measure the similarities between two fingerprints. Since we only take into account the top 10 hypotheses in the verification step, as compared to the linear search, our approach provides a reduction by a factor of 200 for the number of the hypotheses that need to be considered if linear search is used. We achieve promising experimental results on the *NIST-4* database, which has a large portion of poor quality fingerprints.

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