An efficient algorithm for fingerprint matching

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An efficient algorithm for fingerprint matching

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Abstract

This paper proposes novel topology-based algorithms for fingerprint matching. Three major aspects of fingerprint matching are considered: local matching, tolerance to deformation and global matching. The approach improves both the accuracy and the speed of fingerprint identification. Computational geometry methods including Delaunay triangulation and spatial interpolation are used. The proposed methods are able to efficiently deal with the distortions of fingerprints. Experimental results confirm that the algorithms presented are effective and more efficient compared to other fingerprint matching algorithms.

1. Introduction

Fingerprint identification is one of the most powerful biometric tools for ensuring national and personal security, confidential data protection and legitimate use of computer systems. A fingerprint matching algorithm compares two fingerprint images and return either a degree of similarity or a binary decision of matched or not matched. A large number of automatic fingerprint matching algorithms have been proposed. They can be coarsely classified into three families: correlation-based matching, minutiae-based matching and other features based matching.

Given a fixed set of computational resources, minutiae-based matching is considered to be the best, with the highest matching capability. However, there are a couple of challenges for this approach that will be addressed in this paper:

- Missing and spurious minutiae must be taken into consideration. In other words, the matching algorithm must accommodate points in one set that do not have a corresponding point in the other set.
- General minutiae-based matching methods are computationally expensive.
- The difficulty for minutiae-based methods is nonlinear deformations of fingerprints. If the deformations are not explicitly modeled, a perfect alignment of the point sets will not be possible. In this case, the alignment algorithm must try to find the optimal alignment according to some criteria.

The topology-matching algorithm in this paper is based on three novel ideas. First, for the choice of the matching index, Delaunay triangle edges are used rather than minutiae or whole minutiae triangles. Second, a new deformation model is applied, which helps to deal with the elastic finger deformations that sometimes are very harmful in fingerprint verification. Third, to get a better matching performance, a maximum bipartite matching scheme is applied for the matching accuracy improvement.

2 Local Structure Matching and Deformation Modelling

The purpose of fingerprint verification is to determine whether two fingerprint images are from the same finger or not. In order to do this, the input fingerprint has to be aligned with the template fingerprint represented by its minutia pattern. Under a simple rigid transformation, a input fingerprint can be transformed to its template fingerprint after rotating by $\Delta\theta$ and translating by $(\Delta x, \Delta y)$.

Delaunay triangle edge are used as the comparison index to obtain the transformation. The Voronoi diagrams and Delaunay triangulations approaches were originally introduced to study proximity relationship among objects in space. Here, Delaunay triangulation is applied to the minutiae and the resulting Delaunay triangulation is referred as the minutiae graph. This graph contains all the topological properties of the Delaunay triangulation. It tells which vertices are connected, and it also contains the geometric measures, such as the lengths of the edges and the angles at each vertex (see Fig.1 (b)).

When two edges match successfully with roughly equal length, $\theta 1$ and $\theta 2$, transformation parameters $(\Delta\theta, \Delta x, \Delta y)$ are obtained by comparing the corresponding minutiae pairs of these two edges.

For two images, there are possible more than one matched triangle edge pairs. For each matched triangle edge

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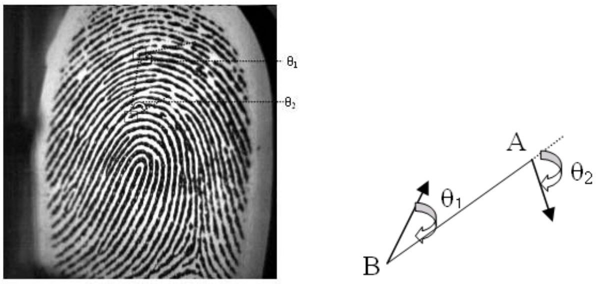


(a) θ (b) Triangle edge

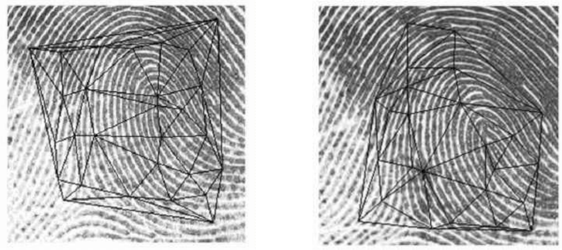
Figure 1. Minutiae triangle edge

pair, we can obtain a transformation triple $(\Delta\theta_i, \Delta x_i, \Delta y_i)$. These recorded transformations are close to each other, but not identical. If minutiae in the input image have the identical transformation or we use the average transformation parameters $(\Delta\theta, \Delta x, \Delta y)$ in global matching, that is the rigid transformation and we do not need to consider the deformation. Unfortunately, fingers are elastic and deformation exists when images are taken.

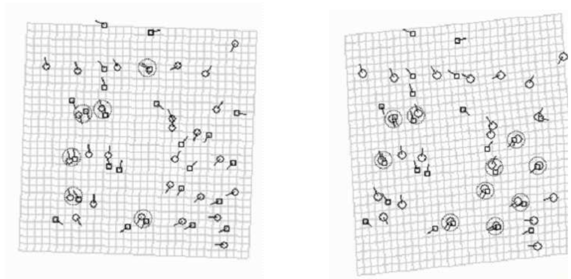
A good fingerprint identification system will always compensate for these deformations. We develop a simple framework aimed at approximately quantifying and modeling the local, regional and global deformation of the fingerprint. We propose to use the Radial basis functions (RBF), which represent a practical solution to the problem of modeling of a deformable behavior. The application of RBF has been explored in medical image matching and image morphing [3, 7]. But to the best of our knowledge, it has not been applied for fingerprint verification. In the followings, RBF methods are proposed and applied to fingerprint matching.

For our fingerprint matching algorithm, deformation problem can be described as: knowing the consistent transformations of some points which we call control points in the minutiae set of input image, how to interpolate the transformation of other minutiae which are not control points. We do not consider all the transformations obtained by the local matching. We vote for them in the transformation space and pick those consistent transformations which form large clusters.

The application of deformation model can help us to match two corresponding images with a higher accuracy. Fig.2 (a) and (b) show the Delaunay triangulation of minutiae set form input image and template image respectively. If we assume a rigid transformation between these two images, there are maximum 6 matched minutiae pairs (marked by the big dashed circle in Fig.2(c)). Knowing transformation of five minutiae (control points) of input image during local matching, we apply the RBF to model the non-rigid transformation which is visualized by the deformed grid in Fig.2(d). The number of matching minutiae pairs is 10 (labeled by the big dashed circle), which greatly increased the matching scores of these two corresponding images. Experiments in Fig.2 tell us the maximum number of matching minutiae pairs can be increased if we consider that there is a non-rigid transformation between input and template images and apply the RBF to model the deformation. A considerably better matching score can be obtained after we apply it.



(a) Input image (b) Template image



(c) Rigid transformation (d) Non-rigid transformation

Figure 2. Application of RBF to model the fingerprint deformation

3 Maximum Bipartite Matching

The purpose of global matching is to find matching degree of two fingerprint images after registration. Here, we want to match minutiae pairs under known transformation. If one minutiae from input image and one minutiae from template image fall into the same tolerance box (the big dashed circle in Fig.2(c)(d)) after transformation, they are defined as matched. However, to obtain an optimal pairing is not so easy as it looks.

The most important rule of matching feature points is to guarantee one minutia from input image can match to at most one minutia from template image. To comply with this constraint, the minutiae that have already been matched can be marked to avoid matching them twice or more. However, it is hard to find the optimal pairing of the feature points. For example, in Fig.3 the best pairing is the configuration that can maximize the final number of matched minutia pairs. A more sophisticated method should be used to obtain this optimum pairing.

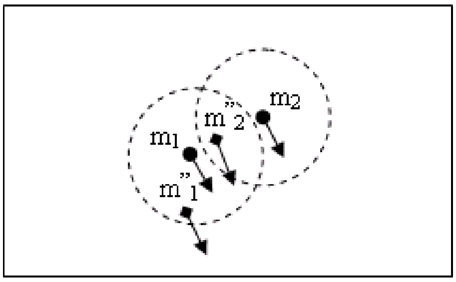


Figure 3. Strategy of matching minutiae pairs. In this example, if m_1 were matched with $m_2^{"}$ (the closest minutiae), m_2 would remain unmatched; however, pairing m_1 with $m_1^{"}$, allows m_2 to be matched with $m_2^{"}$, thus maximizing the matching pairings

We propose using a bipartite weight graph $B = (Q, P)$ to match the minutiae pairs, where Q denotes the set of n minutiae in the input image and P denote the set of m minutiae in template image. For minutiae q in Q and minutiae p in P, if their distance (location and angle) is in tolerance box under known transformation, an edge is built between them. The capacity for these edges is set 1. For edges from source s to q and p to sink t, we set the capacity to 1. Under such setting, the problem of finding the maximum number of matched point pairs between the input and template images is turn to find the maximum flow in this bipartite graph. We use Ford-Fulkerson algorithm provided by T. Cormen et.al.[2] to find the maximum flow in such bipartite graph.

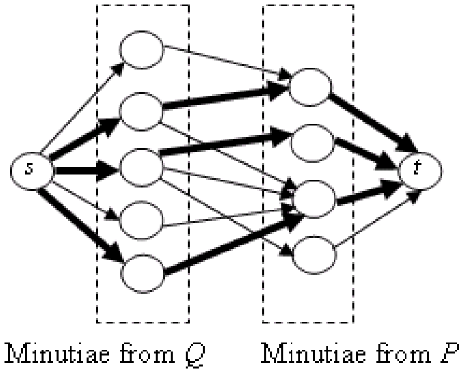


Figure 4. Point pattern matching problem. The edges from s to Q have capacity 1. The edges from P to t have capacity 1. Minutiae from Q and P are connected if these two minutiae are paired, capacity of that edge is 1. The occurrence arrow corresponds to those in a maximum flow or maximum matching pairs of the input and template images. In this example, the maximum number of matched minutiae pair is three.

Delaunay triangulation	Deformation model	Global matching	Total time
$O(nlogn)$	$O(n^2)$	$O(n^2)$	$O(n^2)$

Table 1. Computation complexity of topology-based matching algorithm

4 Experiments and Evaluation

The software we developed was implemented using C++ programming environment and tested on a Celeron 1400MHZ CPU 512 RAM computer. Experiments were conducted on fingerprints from a fingerprint database at University of Bologna, Italy. The fingerprint database consists of 21×8 fingerprint images (containing 8 images per finger from 21 individuals), the quality of images vary significantly and the size of the fingerprint images was 256×256 pixels.

In Table.1, there are three steps in our matching algorithm: local matching, deformation model and global matching. Let n refer to the number of minutiae. The computational complexity for Delaunay triangulation by sweep line method is $O(nlogn)$. In the worst case (there are n control points), the calculation of RBF function and registration takes $O(n^2)$ time. Finally, it take $O(n^2)$ time to match point pairs in global matching. Thus, the computation complexity of our algorithm is $O(n^2)$. It is $O(n^3)$ for most minutiae or minutiae and ridge based methods [4, 5, 6, 8]. Experimental results also prove that our algorithm performs faster than standard methods. Average time of one matching is about 27ms (feature extraction time is not included). Using the same machine and same minutiae sets from feature extraction, average time cost is 98ms for the standard minutiae methods. For standard minutiae methods, we refer to the methods in [4, 6, 8]. In local matching, every possible transformation is tried and only one transformation triple is obtained which maximize the number of matched minutiae pair in global matching.

To evaluate a biometric identification system, there are a couple of criteria, two of which are very important. The FAR (False Accepted Rate) is a statistical measurement of the number of impostors likely to be accepted by a biometric system. The FRR (False Refused Rate) is a statistical and empirical measurement of the likelihood of genuine users being rejected by a system.

In Table.2, we studied the performance of our matching algorithm by comparing with standard matching algorithm.

	FRR	FAR	Time
Standard methods	17.09%	0.84%	$98ms$
Our methods	5.46%	0.19%	$29ms$

Table 2. Accuracy and speed of our matching algorithm

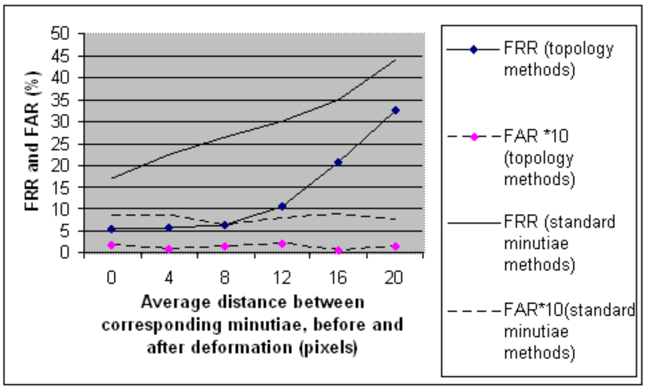


Figure 5. Performance of topology methods vs. standard methods under distortion.

Our method performs very well in speed because we use the triangle edge as our comparison index. The application of RBF to model finger deformation and our improvement to global matching routine greatly increase the matching accuracy.

One of the main difficulties in matching two fingerprint samples of the same finger is to deal with the non linear distortions, often produced by an incorrect finger placement over the sensing element, which make a global rigid comparison unfeasible. To describe our algorithm's robust against the non-linear distortion, we want to conduct more experiments on the distorted images. Thus, we apply a mathematical model [1] to model the real distortion of fingerprint.

We assume that the original images in test database are images without non-linear distortion. In the plastic distortion model, there are three distinct regions in the fingerprint. A close-contact region does not allow any skin slippage. For minutiae points in other two regions, their locations will be changed. The average distance in Fig.5 represent the average distance change of minutiae points in pixels after we distort the images. When there is no distortion, the location of minutiae points does not change and the average distance is 0. The FRR and FAR are 5.46% and 0.19% respectively, which is taken from Table.2. Fig.5 shows that when the distortion is not very significant, i.e: average distance is less than 6 pixels, the accuracy of our matching algorithm remains almost the same. However, the FRR of the standard minutiae methods will increase in a much faster manner than ours. In other words, our algorithm is more robust against the non-linear distortion than the standard methods.

5 Conclusions

We have developed a novel topology-based matching algorithm. The proposed scheme is a Delaunay triangulation based technique. Triangle matching is fast and overcomes the relative non linear deformation problems, because it is independent on the fingerprint rigid transformation. To overcome the relative deformation that is present in the fingerprint image pairs, we also proposed a novel RBF model that is able to deal with elastic distortions. The proposed maximum bipartite matching schema can optimize the global matching. Our experiments show that fingerprint images can be well matched using the topology-based matching method even on fingerprint database with nonlinear distortion.

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