Elastic Minutiae Matching by Means of Thin-Plate Spline Models

Asker M. Bazen and Sabih H. Gerez
University of Twente, Department of Electrical Engineering
P.O. box 217, 7500 AE Enschede, The Netherlands
E-mail: a.m.bazen@el.utwente.nl

Abstract

This paper presents a novel minutiae matching method that deals with elastic distortions by normalizing the shape of the test fingerprint with respect to the template. The method first determines possible matching minutiae pairs by means of comparing local neighborhoods of the minutiae. Next a thin-plate spline model is used to describe the non-linear distortions between the two sets of possible pairs. One of the fingerprints is deformed and registered according to the estimated model, and then the number of matching minutiae is counted. This method is able to deal with all possible non-linear distortions while using very tight bounding boxes. For deformed fingerprints, the algorithm gives considerably higher matching scores compared to rigid matching algorithms, while only taking 100 ms on a 1 GHz P-III machine.

1. Introduction

Fingerprint matching is the task of comparing a *test* fingerprint that is actually provided to a *template* fingerprint that is provided earlier during enrollment. Most fingerprint matching systems are based on the minutiae, which are the endpoints and bifurcations of the line structures in the fingerprint that are called ridges. A minutiae-based fingerprint matching system roughly consists of two stages. In the *minutiae extraction* stage, the minutiae are extracted from the gray-scale fingerprint, while in the *minutiae matching* stage, two sets of minutiae are compared in order to decide whether the fingerprints match. Minutiae matching is the subject of this paper.

In minutiae matching, two stages can be distinguished. First, *registration* aligns both fingerprints as well as possible. Most algorithms use a combination of translation, rotation and scaling for this task. After registration, the matching score is determined by *counting* the corresponding minutiae pairs between both fingerprints. Two minutiae correspond if a minutia from the test set is located within a *bounding box* or *tolerance zone* around a minutia from the template set. The matching score, which is a number in the range from 0 to 1, is calculated as the ratio of the number of matched minutiae to the total number of minutiae.

Unfortunately, there are a lot of complicating factors in minutiae matching. First, both sets may suffer from false, missed and displaced minutiae, caused by imperfections in the minutiae extraction stage. Second, the two fingerprints to be compared may originate from a different part of the same finger, which means that both sets overlap only partially. Third, the two prints may be translated, rotated and scaled with respect to each other. The fourth problem is the presence of non-linear plastic distortions or elastic deformations in the fingerprints, which is the most difficult problem to solve. These distortions are caused by the acquisition process itself. During capturing, the 3-dimensional elastic surface of a finger is pressed on a flat sensor surface. This 3D-to-2D mapping of the finger skin introduces non-linear distortions, especially when forces are applied that are not orthogonal to the sensor surface. The effect is that the sets of minutiae of two prints of the same finger no longer fit exactly after rigid registration. This is illustrated in Figure 1(a) where the ridge skeletons of two prints of the same finger are registered optimally and depicted in one figure.

In order to tolerate minutiae pairs that are further apart because of plastic distortions, and therefore to decrease the false rejection rate (FRR), the size of the bounding boxes can be increased. However, as a side effect, this gives non-matching minutiae pairs a higher probability to get paired, resulting in a higher false acceptance rate (FAR). Therefore, changing the size of the bounding box around minutiae only has the effect of exchanging FRR for FAR, while it does not solve the problem of plastic distortions.

Recently, some methods were presented that deal with the problem of matching elastically distorted fingerprints more explicitly, thus avoiding the exchange of error rates. The ideal way to deal with distortions would be to invert the 3D-to-2D mapping and compare the minutiae positions in 3D. Unfortunately, there is no unique way of inverting this mapping. It is therefore reasonable to consider meth-

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ods that explicitly attempt to model and eliminate the 2D distortion in the fingerprint image. In [10], a method is proposed that first estimates the local ridge frequency in the entire fingerprint and then adapts the extracted minutiae positions in such a way that the ridge distances are normalized all over the image. Although the stricter matching conditions increase the performance of the matching algorithm slightly, this method only solves some specific part of the non-linear deformations.

The fact that no reference without distortion is available makes normalization in 2D a relative rather than an absolute matter. Instead of normalizing each fingerprint on its own, the non-linear distortions of one fingerprint with respect to the other have to be estimated and eliminated. In [4], the physical cause of the distortions is modelled. Experiments have shown that this model provides an accurate description of the plastic distortions in some cases. However, the model has not yet been used in a fingerprint-matching algorithm. Accurate estimation of the distortion parameters is still a topic of research.

In this paper, a minutiae matching algorithm is presented that is able to deal with elastically distorted fingerprints by using a non-linear registration algorithm. It models the distortions based on the locations and orientations of the extracted minutiae. As a consequence, the distances between the corresponding minutiae are much smaller and stricter thresholds can be used in the counting stage. This results in an algorithm that is able to decrease FAR and FRR simultaneously.

This paper is organized as follows. First, in Section 2, the elastic minutiae matching algorithm is explained. Next, in Section 3, experimental results of the elastic minutiae matching algorithm are given.

2. The Matching Algorithm

The elastic minutiae matching algorithm estimates the non-linear transformation model in two stages. First, the local matching that is presented in Section 2.1 determines which minutiae possibly match, based on local similarity measures. Without this stage, a problem with too many degrees of freedom would have to be solved. Next, the global matching that is presented in Section 2.2 uses the possible correspondences to estimate a global non-rigid transformation. After registration, the corresponding minutiae are counted using thresholds that can be chosen rather strictly since the distance between corresponding minutiae after elastic registration is small.

2.1. Local Matching

The first step in the proposed matching algorithm is the comparison of local structures. These structures can be compared easily since they contain few minutiae in a small area. In addition, since the structures represent only a small area in a fingerprint, they are unlikely to be seriously deformed by plastic distortions. The local matching algorithm was inspired by the approach that was described in [6].

Each minutia in the template and test fingerprints is described by parameters (x, y, θ), where (x, y) are the pixel coordinates of the minutia and θ is orientation of the minutia, that is calculated using the directional field [2]. Each minutia defines a number of local structures, called *minutia neighborhoods*, consisting of the minutia itself and two close neighboring minutiae.

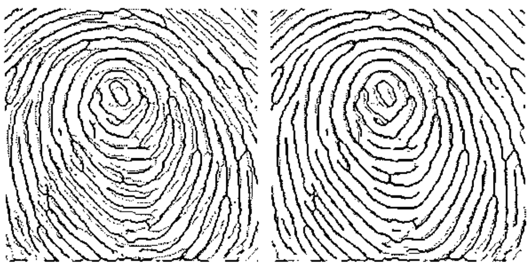
The local matching algorithm compares each minutia neighborhood in the test fingerprint to each minutia neighborhood in the template fingerprint. First, the two structures are aligned using a least squares algorithm that determines the optimal rotation, translation and scaling. Next, the scaling, the sum of the squared distances between the corresponding minutiae and the differences of the directional fields at the minutiae locations are used to measure the similarity of the two minutia neighborhoods. If the structures are considered to match, the transformation (t, r, s), consisting of translation $t = (t_x, t_y)$, rotation r and scaling s, is stored.

After each minutia neighborhood in the test fingerprint has been compared to each minutia neighborhood in the template fingerprint, a list of corresponding minutiae pairs is obtained. Note that this list does not contain all true correspondences and that inclusion in this list does not necessarily indicate a true correspondence.

2.2. Global Matching

The next step is the determination of the global transformation that optimally registers the two fingerprints. This is called the global matching stage. From the list of local similarities, the global transformation is determined that matches the largest number of local matching pairs. It is expected that this transformation also matches the largest number of minutiae from the entire sets.

Several strategies to determine the optimal global transformation from the list of local transformations exist. The main problem is caused by the false and contradictory local matches. In [6], the transformation of the single minutia neighborhood pair that matches best, is taken. However, using more information of other local matches will certainly improve the accuracy of the registration. Another possibility is to quantize the local registration parameters into bins and construct an accumulator array that counts all occurrences of each quantized registration. Next, the registration that occurs most is selected, and the average of all registrations in that bin is taken. This strategy roughly corresponds to the work of [5].



(a) Rigid registration (b) TPS registration

Figure 1. Ridge skeletons of elastically distorted fingerprints that are registered by means of rigid and TPS algorithms.

Further improvement is achieved by determining the optimal registration parameters from the positions of the matching minutia neighborhoods instead of averaging the individual registration parameters. First, the largest group of pairs that share approximately the same registration parameters is selected. Next, the optimal transformation for registering the test set to the template set is calculated in a least squares sense. This gives the optimal registration (t, r, s) for the selected minutia neighborhoods.

However, when applying this registration, deformed fingerprints will not be registered well, as shown in Figure 1(a), simply because an accurate (t, r, s) registration does not exist. This has to be compensated for in the counting stage. It has been reported in [8] that for 97.5% of the minutiae to match, a threshold of $r_0 = 15$ pixels has to be used in 500 dpi fingerprints. As a consequence, minutiae in a rather large part of the image (25% for 30 minutiae in a 300×300 image) are considered to match even when they actually do not match.

In order to allow stricter matching, i.e. a smaller value of r_0, non-linear registration has to be used to compensate for plastic distortions. A transformation that is able to represent elastic deformations is the *thin-plate spline* (TPS) model [3]. To our knowledge, it has not been applied earlier to fingerprint recognition. The TPS model describes the transformed coordinates (x', y') both independently as a function of the original coordinates (x, y):

$$(x', y') = (f_x(x, y), f_y(x, y)) \quad (1)$$

Given the displacements of a number of landmark points, the TPS model interpolates those points, while maintaining maximal smoothness. The smoothness is represented by the bending energy of a thin metal plate. At each landmark point (x, y), the displacement is represented by an additional z-coordinate, and, for each point, the thin metal plate is fixed at position (x, y, z). The bending energy is given by the integral of the second order partial derivatives over the entire surface and can be minimized by solving a set of linear equations. Therefore, the TPS parameters can be found very efficiently. The TPS model for one of the transformed coordinates is given by parameter vectors $\mathbf{a}$ and $\mathbf{w}$:

$$f(x, y) = a_1 + a_2 x + a_3 y + \sum_{i=1}^{n} w_i U(|P_i - (x, y)|) \quad (2)$$

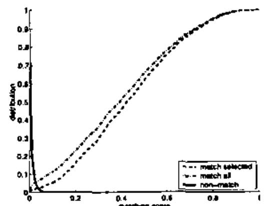
where $U(r) = r^2 \log r$ is the basis function, $\mathbf{a} = [a_1\, a_2\, a_3]^T$ defines the affine part of the transformation, $\mathbf{w}$ gives an additional non-linear deformation, and the P_i are the landmarks that the TPS interpolates. Note that this equation does not indicate how to calculate the TPS parameters.

In [9], a method is presented to estimate *approximating thin-plate splines*. These splines do not exactly interpolate all given points, but are allowed to approximate them in favor of a smoother transformation. The smoothness is controlled by a parameter λ, which weights the optimization of landmark distance and smoothness. For $\lambda = 0$, there is full interpolation, while for very large λ, there is only an affine transformation left.

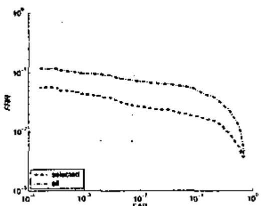
In fingerprint matching, it is essential to use approximating thin plate splines, since this introduces some insensitivity to errors. For instance, minutiae may be displaced a few pixels by the minutiae extraction algorithm or false local matches may be included into the global matching stage. Interpolating TPS will include these displacement errors into the registration exactly, resulting in strange unsmooth transformations and incorrect extrapolations. Obviously, a smoother transformation that does not take all small details into account is much more robust. In that case, the TPS registration represents the elastic distortions, while in the counting stage, the threshold r_0 takes care of local minutiae displacements.

The TPS model is fitted in a number of iterations. First, an initial model is fitted to the local matches. Next, the corresponding minutiae are counted and a new model is fitted to those corresponding minutiae. This is repeated until the model has converged to its final state. This improves the quality of the non-linear registration considerably and increases the matching score significantly.

The two deformed fingerprints of Figure 1(a) are shown in Figure 1(b) after registration by means of thin-plate splines. The figure clearly shows the much more accurate registration. This means that a much lower threshold r_0 can be used in the counting stage, leading to a considerably lower false acceptance rate.



(a) Distributions



(b) ROC

Figure 2. Results of the TPS-based matching algorithm on database 2 of FVC2000, with and without discarding low-quality fingerprints.

3. Results

The proposed algorithm has been evaluated by applying it to the second FVC2000 database [7]. This database consists of 880 capacitive 8-bit gray-scale fingerprints, 8 prints of each of the 110 fingers. The images are captured at 500 dpi, resulting in image sizes of 364×256 pixels.

Unfortunately no benchmark results are available in the literature to measure the performance of minutiae-based matching for given fixed sets of minutiae. Any result reported on a database such as the one of FVC2000 incorporates the performance of a minutiae extraction stage, which is not a topic of this paper. However, for the sake of the experiments, a straightforward method was implemented consisting of enhancement, Gabor filtering, binarization, thinning and postprocessing [1].

The TPS-based elastic matching has been compared to rigid matching, which is the common method in minutiae matching. In both cases, r_0 was chosen such that the matching performance was optimized. To compensate for the simple minutiae extraction, experiments have been done with the entire database and with a selection of 90% of the highest quality prints. With $r_0 = 15$ for rigid matching and $r_0 = 5$ for elastic matching the equal-error rates of the ROC turned out to become 4% and 2% respectively. The distributions of the matching scores and the ROC for the elastic matching experiment are shown in Figure 2.

The proposed elastic matching algorithm is rather fast. Whereas most elastic matching algorithms take several minutes, the entire elastic minutiae matching algorithm takes less than 100 ms, using a C++ implementation on a 1 GHz P-III machine. Furthermore, it is only marginally more complex than the rigid matching algorithm. The local matching stage takes approximately 50 ms, rigid matching would take 10 ms and elastic matching takes 30 ms.

4. Conclusions

This paper has proposed a novel minutiae matching algorithm that is able to deal with elastic distortions of fingerprints. Using thin-plate splines, the algorithm handles all possible non-linear distortions while using very tight bounding boxes. It has been shown that it is able to register distorted fingerprints very well. When applied to elastically deformed fingerprints, the elastic matching algorithm provides considerably better matching scores than rigid matching algorithms. Since a relatively simple minutiae extraction algorithm was used, it is expected that the matching performance can be improved by linking the proposed matching algorithm to better minutiae extraction algorithms.

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