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Fingerprint matching by thin-plate spline modelling of elastic deformations

Asker M. Bazen*, Sabih H. Gerez

Department of Electrical Engineering, University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands

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Abstract

This paper presents a novel minutiae matching method that describes elastic distortions in fingerprints by means of a thin-plate spline model, which is estimated using a local and a global matching stage. After registration of the fingerprints according to the estimated model, the number of matching minutiae can be counted using very tight matching thresholds. 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. Furthermore, it is shown that the observed deformations are different from those described by theoretical models proposed in the literature.

Keywords: Fingerprint verification; Minutiae matching; Elastic deformations; Thin-plate spline models; Registration

1. Introduction

Recognition of persons by means of biometric characteristics is an emerging phenomenon in our society. It has received more and more attention during the last years due to the need for security in a large range of applications. Among the many biometric features, the fingerprint is considered one of the most practical ones. Fingerprint recognition requires a minimal effort from the user, does not capture other information than strictly necessary for the recognition process and provides relatively good performance. Another reason for the popularity of fingerprints is the relatively low price of fingerprint sensors, which enables easy integration into PC keyboards, smart cards and wireless hardware.

Even when many academic and commercial systems for fingerprint recognition exist, there is a necessity for further research in the topic in order to improve the reliability and performance of the systems. Noise in the captured fingerprint image, plastic distortion of the skin when pushing the finger onto the sensor, the partial image of a finger that is obtained, large fingerprint databases, etc. make it difficult to achieve high performance figures for fingerprint recognition systems. The development of better algorithms can reduce the error rates to levels that are acceptable for a wide range of applications.

The topic of this paper is fingerprint matching, which 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 elevated 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. This paper deals with the compensation of elastic distortions for the sake of improving the performance of minutiae matching.

In minutiae matching, two stages can be distinguished. First, *registration* aligns both fingerprints as well as

* Corresponding author. Tel.: +31-53-489-3156; fax: +31-53-489-1060.

E-mail addresses: a.m.bazen@el.utwente.nl (A.M. Bazen), s.h.gerez@el.utwente.nl (S.H. Gerez).

URL: http://www.sens.el.utwente.nl

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possible. Most algorithms use a combination of translation, rotation and scaling for this task. In the rest of this paper, a transformation that is based on rotation, translation and scaling only will be called *rigid*. A non-rigid transformation for registration will be called *elastic*. 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 number of matched minutiae divided by the total number of minutiae.

Unfortunately, there are a lot of complicating factors in minutiae matching. First of all, 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. This problem is addressed in this paper.

This paper is organized as follows. First, in Section 2, elastic deformations are discussed and an overview is given of other matching methods that try to deal with them. Next, in Section 3, an elastic minutiae matching algorithm is proposed that estimates a deformation model and uses this model for improved minutiae matching. Finally, in Section 4, experimental results of the elastic minutiae matching algorithm are given.

2. Elastic deformations

Elastic distortions are caused by the acquisition process itself. During capturing, the three-dimensional (3D) elastic surface of a finger is pressed onto a flat sensor surface. This 3D–2D mapping of the finger skin introduces non-linear distortions, especially when forces are applied that are not orthogonal to the sensor surface. This is a realistic situation when dealing with non-cooperative users that deliberately apply excessive force in order to create intentional elastic deformations. 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 the leftmost part of Fig. 3 where the ridge skeletons of two prints of the same finger have been registered optimally and displayed 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), most algorithms increase the size of the bounding boxes [1]. 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. An alternative approach is to use only local similarity measures, as addressed in Section 3.1, since those are less affected by plastic distortions [2,3]. However, this also decreases the required amount of similarity, and therefore also exchanges FRR for FAR.

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–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 methods that explicitly attempt to model and eliminate the 2D distortion in the fingerprint image. In Ref. [4], 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 slightly increase the performance of the matching algorithm, this method only solves some specific part of the non-linear deformations.

Since it is not known in advance whether captured fingerprints contain any distortion, true normalization of the fingerprints to their genuine shape is not possible. 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 Ref. [5], the physical cause of the distortions is modelled by distinguishing three distinct concentric regions in a fingerprint. In the center region, it is assumed that no distortions are present, since this region tightly touches the sensor. The outer, or external, region is not distorted either, since it does not touch the sensor. The outer region may be displaced and rotated with respect to the inner region, due to the application of forces while pressing the finger at the sensor. The region in between is distorted in order to fit both regions to each other, as shown in Fig. 1. Experiments have shown that this model provides an accurate description of the plastic distortions in some cases. The technique has successfully been applied to the generation of many synthetic fingerprints of the same finger [6]. However, the model has not yet been used in an algorithm for matching fingerprints. Accurate estimation of the distortion parameters is still a topic of research.

Furthermore, a number of non-rigid registration methods have been proposed in other fields than fingerprint matching, see e.g. Refs. [7,8]. Most of these methods, however, suffer from two problems. First, they assume that the correspondences between two sets of points are known from the local image structure around these points, which is not a realistic assumption in fingerprint matching where all minutiae points look similar. In addition, they require much processing time, ranging from 1 to several minutes. In

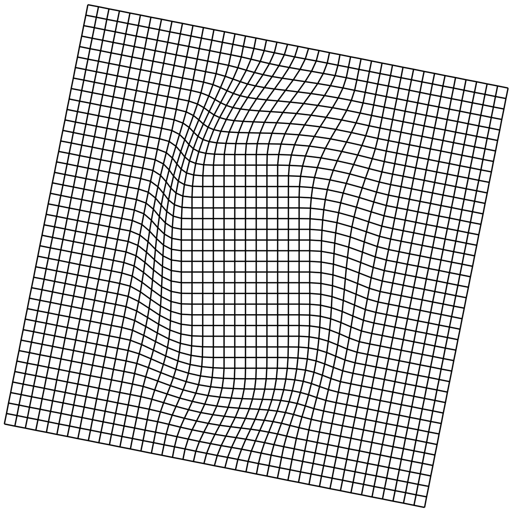


Fig. 1. Elastic deformation model of Ref. [5].

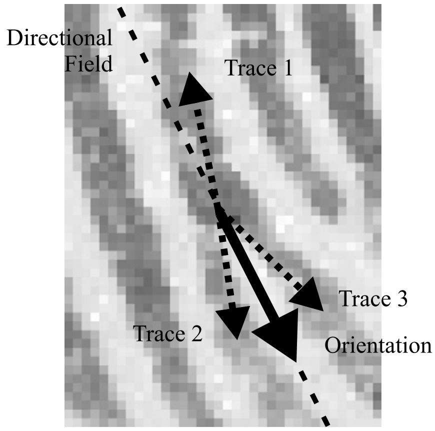


Fig. 2. Estimation of the minutiae orientation.

fingerprint matching the available time is limited to only a few seconds. Therefore, these methods cannot be applied to the fingerprint matching problem.

In this paper, a minutiae matching algorithm is presented that models elastic distortions by means of a thin-plate spline model, based on the locations and orientations of the extracted minutiae. This model is used to normalize the shape of the test fingerprint with respect to the template. It is therefore able to deal with elastically distorted fingerprints. As a consequence, the distances between the corresponding minutiae are much smaller and tighter bounding boxes can be used in the counting stage. This results in an algorithm that is able to decrease FAR and FRR simultaneously.

3. 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 3.1, 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 3.2, uses the possible correspondences to estimate a global non-rigid transformation. After registration, the corresponding minutiae are counted using bounding boxes that can be chosen rather strictly since the distance between corresponding minutiae after elastic registration is small.

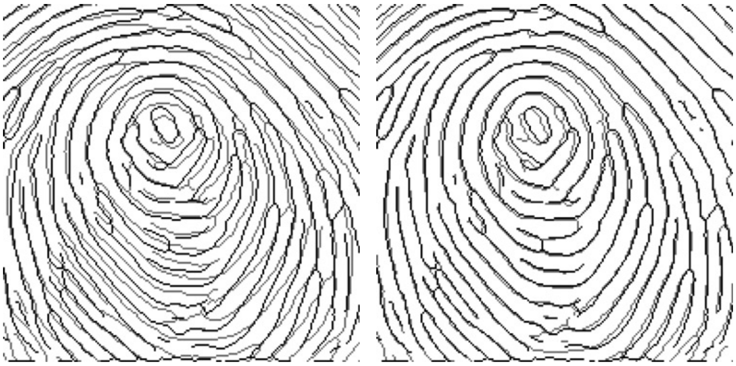
3.1. Local matching

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 originate from 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 Ref. [9].

Each minutia m 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 the orientation of the minutia. The orientation is estimated by tracing the all ridges from the minutia over some distance (1 ridge for an endpoint and 3 ridges for a bifurcation) and quantizing the obtained ridge directions to the directional field [10] or the opposite direction. For an endpoint, this directly gives the orientation and for a bifurcation, the orientation that occurs twice is selected. This is illustrated in Fig. 2. The matching algorithm does not distinguish endpoints from bifurcations since the type of a minutia can be easily interchanged by acquisition noise or pressure differences during acquisition. However, the orientation remains the same when this occurs.

Each minutia defines a number of local structures, which are called *minutia neighborhoods*. A minutia neighborhood consists of the minutia itself and two neighboring minutiae. When the reference minutia is called m_0 and its closest neighbors with increasing distance from m_0 are $m_1, m_2, \ldots, m_{n-1}$, with n the number of minutiae, the neighborhoods $\{m_0, m_1, m_2\}$, $\{m_0, m_1, m_3\}$ and $\{m_0, m_2, m_3\}$ are selected for each minutiae. Compared to selecting only one neighborhood, this provides more robustness in the local matching stage with respect to false and missing 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, a local matching decision is made by comparing the scaling, the sum of the squared distances between the corresponding



(a) (b)

Fig. 3. Ridge skeletons of elastically distorted fingerprints that are registered by means of rigid (a) and thin-plate spline (b) algorithms.

minutiae, and the differences of orientation to a threshold. If the structures are considered to match, the pair of minutia neighborhoods and 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 minutia neighborhood 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. However, its size gives a first indication of the degree of similarity of the two fingerprints.

3.2. 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 correspondences, the global transformation is determined that is consistent with the largest number of matching minutia neighborhood pairs. It is expected that this transformation explicitly selects the largest number of matching minutiae pairs from the entire minutiae sets.

Several strategies to determine the optimal global transformation from the list of local transformations exist. Those methods mainly differ in handling the difficulty of false and contradictory local matches. In Ref. [9], 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 bin that occurs most is selected, and the average of all registrations in that bin is taken. This strategy roughly corresponds to the work of Ref. [11], although that method is not based on matching local minutia neighborhoods.

The method that is proposed here, achieves further improvement 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. This is achieved by determining for each matching pair the number of pairs of which the registration parameters differ less than a certain threshold. Next, the transformation (t, r, s) that optimally registers the selected minutiae in the test set to the corresponding minutiae in template set is calculated in a least squares sense.

However, when applying this registration, elastically deformed fingerprints will not be registered well, as shown in Fig. 3, simply because an accurate registration (t, r, s) does not exist. Most matching algorithms compensate this in the counting stage. It has been reported in Ref. [1] that for 97.5% of the minutiae to match, a threshold on the Euclidean distance of two minutiae 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% of the image 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, elastic 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 [12]. 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):

$$x' = f_x(x, y), \tag{1}$$

$$y' = f_y(x, y). \tag{2}$$

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 **a** and **w**:

$$f(x, y) = a_1 + a_2 x + a_3 y + \sum_{i=1}^{n} w_i U(|P_i - (x, y)|), \tag{3}$$

where $U(r) = r^2 \log r$ is the basis function, **a** defines the affine part of the transformation, **w** gives an additional non-linear deformation, P_i are the landmarks that the TPS interpolates, and n is the number of landmarks.

The TPS parameters that minimize the bending energy can be found by solving a set of linear equations:

$$\mathbf{K}\mathbf{w} + \mathbf{P}\mathbf{a} = \mathbf{v}, \tag{4}$$

$$\mathbf{P}^{\mathrm{T}}\mathbf{w} = 0, \tag{5}$$

where

$$\mathbf{w} = [w_x(1) \quad w_x(2) \quad \cdots \quad w_x(n)]^{\mathrm{T}}, \tag{6}$$

$$\mathbf{v} = [q_x(1) \quad q_x(2) \quad \cdots \quad q_x(n)]^{\mathrm{T}}, \tag{7}$$

$$\mathbf{a} = [a_x(1) \quad a_x(2) \quad a_x(3)]^{\mathrm{T}}, \tag{8}$$

$$\mathbf{P} = \begin{bmatrix} 1 & p_x(1) & p_y(1) \\ 1 & p_x(2) & p_y(2) \\ \vdots & \vdots & \vdots \\ 1 & p_x(n) & p_y(n) \end{bmatrix}, \tag{9}$$

$$\mathbf{K} = \begin{bmatrix} U(|P_1 - P_1|) & U(|P_1 - P_2|) & \cdots & U(|P_1 - P_n|) \\ U(|P_2 - P_1|) & \ddots & & \vdots \\ \vdots & & \ddots & \vdots \\ U(|P_n - P_1|) & \cdots & \cdots & U(|P_n - P_n|) \end{bmatrix}, \tag{10}$$

$P_i = (p_x(i), p_y(i))$ is the set of landmark points in the first image, $p_x(i)$ is the x-coordinate of point i in set P_i, $Q_i = (q_x(i), q_y(i))$ is the set of corresponding points in the second image, and n is the number of landmark points.

In Ref. [13], 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.

For equal isotropic errors at all landmarks, the optimal TPS parameters can be found by solving the following system of equations:

$$(\mathbf{K} + \lambda\mathbf{I})\mathbf{w} + \mathbf{P}\mathbf{a} = \mathbf{v}, \tag{11}$$

$$\mathbf{P}^{\mathrm{T}}\mathbf{w} = 0, \tag{12}$$

where **I** is the $n \times n$ identity matrix.

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 un-smooth 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 minutiae in the minutia neighborhood pairs that were found in the local matching stage. Next, the corresponding minutiae in both sets, differing in location and orientation less than a threshold, are determined and a new model is fitted to those corresponding minutiae. This is repeated with a decreasing threshold r_0 until the model has converged to its final state. This iterative process improves the quality of the non-linear registration considerably and increases the matching score significantly. Finally, the matching score S is calculated by

$$S = \frac{n_{\mathrm{match}}^2}{n_1 n_2}, \tag{13}$$

where n_{match} is the number of matching minutiae, n_1 the number of minutiae in the test fingerprint and n_2 the number of minutiae in the template fingerprint. This expression provides the most consistent matching scores when the numbers of minutiae in both fingerprints n_1 and n_2 are significantly different, as illustrated in the next paragraph. The match or non-match decision is then taken by comparing the matching score to a threshold.

The difference between the traditional and proposed expressions for determination of the matching score is illustrated by considering the two cases that are given in Table 1. Clearly, case 2 represents a better match, since the algorithm was able to match every minutia of fingerprint 2. However, the traditional matching score is equal to the score in case 1. The proposed matching score expression is able to give case 2 a higher matching score than case 1.

Table 1
Comparison of matching score expressions

	n_1	n_2	n_{match}	$\frac{n_{\text{match}}^2}{n_1 n_2}$	$\frac{2n_{\text{match}}}{n_1+n_2}$
Case 1	40	40	20	0.25	0.5
Case 2	60	20	20	0.33	0.5

The rightmost part Fig. 3 shows the two deformed fingerprints after registration by means of thin-plate splines. The figure clearly shows the much more accurate registration with respect to the leftmost part. This means that a much lower threshold r_0 can be used in the counting stage, leading to a considerably lower false acceptance rate.

4. Results

The proposed algorithm has been evaluated by applying it to Database 2 of FVC2000 [14] and training Database 1 of FVC2002. The FVC2000 database consists of 880 capacitive 8-bit gray-scale fingerprints, 8 prints of each of 110 distinct fingers. The images are captured at 500 dpi, resulting in image sizes of 364×256 pixels. The FVC2002 database contains 80 8-bit gray-scale fingerprints, 8 prints of 10 fingers, captured with an optical sensor at 500 dpi.

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 databases such as the ones of FVC2000 incorporate 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

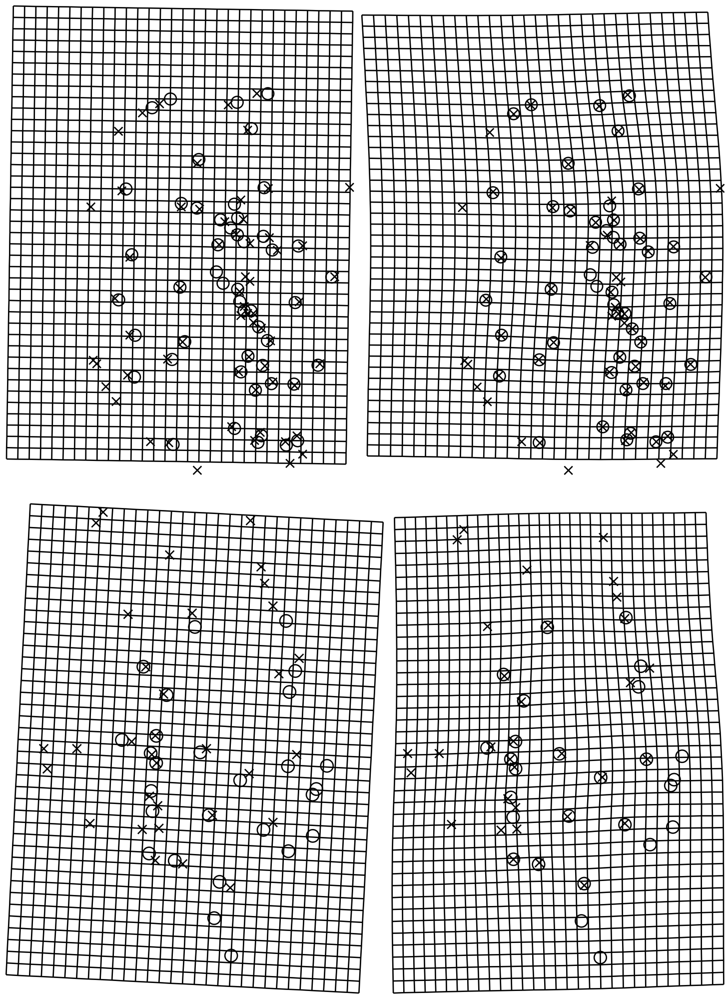


Fig. 4. Registration results for the elastic matching algorithm: the superposition of both minutiae sets (indicated by '×' and '○') and a grid that visualizes the deformations. Top row: typical distortions, bottom row: heavy distortions, left column: rigid registration, right column: TPS registration.

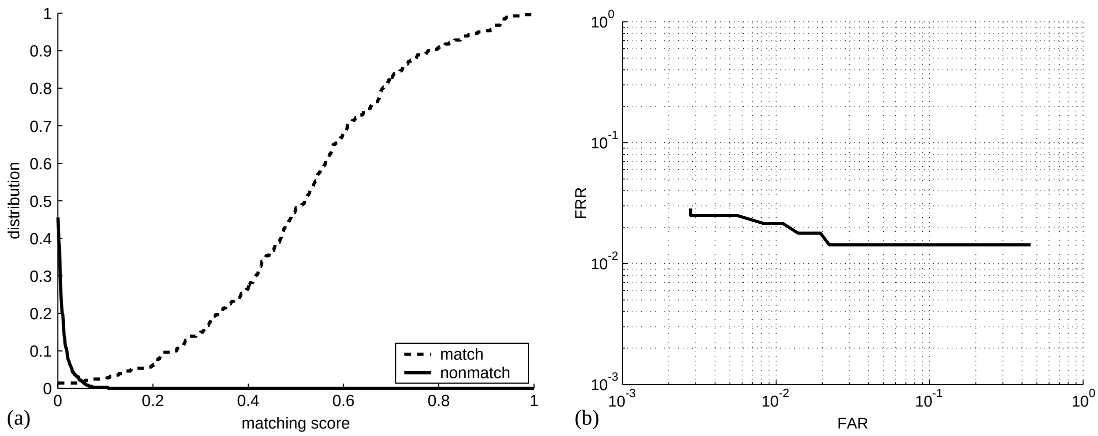


Fig. 5. Results of the TPS-based matching algorithm on training database 1 of FVC2002: (a) matching score distribution, (b) ROC.

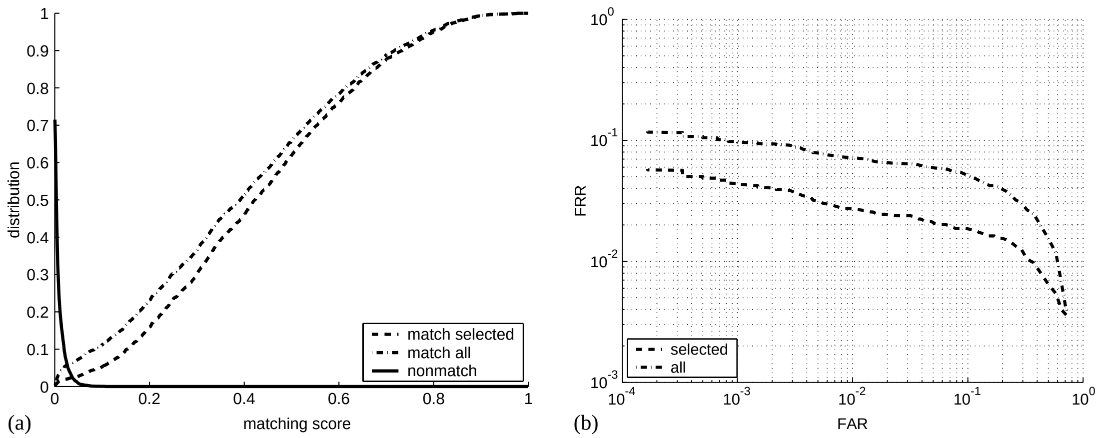


Fig. 6. Results of the TPS-based matching algorithm on database 2 of FVC2000, with and without discarding low-quality fingerprints: (a) matching score distribution, (b) ROC.

consisting of segmentation, Gabor filtering, binarization, thinning and postprocessing [15].

First, the estimated elastic deformation models have been evaluated visually. In Fig. 4, the registration results are depicted for typical and heavy distortions in the FVC2000 database. The figure shows the superposition of both minutiae sets (indicated by '$\times$' and '$\circ$') and a grid that visualizes the deformations. The figures clearly shows that elastic registration makes the minutiae sets fit much better, i.e. the corresponding '$\times$'s and '$\circ$'s are much closer to each other, while the fingerprints are not heavily distorted. For the upper row, the matching scores are 0.42 for the rigid registration and 0.68 for the TPS registration, while the scores for the bottom row are 0.04 and 0.25. Furthermore, it is worth noticing that all distortion patterns that we inspected were similar to the patterns that are shown in Fig. 4, while none of them resembled the distortion model that was proposed in Ref. [5].

Next, due to the lack of benchmark results for minutiae matching performance, it was decided to compare TPS-based elastic matching to rigid matching. In both cases, r_0 was chosen such that the matching performance was optimized. 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 1.8%, respectively for training Database 1 of FVC2002. In this experiment, 280 matches and 450 non-matches have been evaluated. The distributions of the matching scores and the ROC for the elastic matching experiment are shown in Fig. 5.

To evaluate the matching performance of the elastic matching algorithm on database 2 of FVC2000, two experiments have been done. The first experiment considers all fingerprints in the database, leading to 3080 matches and 5995 non-matches. In this case, the equal error rate is 6%. In the second experiment, 10% of the fingers with lowest quality fingerprints have been left out. This compensates for the imperfections in the used minutiae extraction algorithm, and allows better evaluation of only the elastic matching algorithm. In this case, the equal error rate is 2.5%. The matching score distributions and ROCs are shown in Fig. 6.

The combined local and global matching algorithm is able to keep the matching scores for non-matching fingerprints very low: values larger than $S = 0.1$ have never been observed. However, some low matching scores have been observed for matching fingerprints, resulting in a fixed lower bound for FRR, relatively independent of the chosen FAR.

Analysis of these cases resulted in two possible causes for the low matching scores. The first cause is due to imperfections in the used minutiae extraction stage. Low-quality regions are discarded by the segmentation that precedes the minutiae extraction, leading to very few corresponding minutiae. It is expected that the matching performance increases when combined with better minutiae extraction algorithms. The second cause is a very small overlapping region between the two fingerprints that are matched. In this case too, there are only very few corresponding minutiae. This problem was partially solved by determining the rectangular overlapping region from the corresponding minutiae pairs, and using only the minutiae in that region for calculation of the matching score, i.e. adjusting n_1 and n_2 in Eq. (13). However, this may also lead to higher non-matching scores.

Furthermore, it is worth noticing that none of the low-matching scores is caused by the presence of plastic deformations. The algorithm correctly resolves these distortions, while in some cases, the rigid matching algorithm is not able to do so.

Finally, the proposed elastic matching algorithm is rather fast. In a C++ implementation on a 1 GHz P-III machine, the entire elastic minutiae matching algorithm takes less than 100 ms. 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.

5. 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.

The algorithm detected only relatively small elastic deformations. Furthermore, it seems that distortion patterns encountered in practice do not resemble much the models that were proposed in Ref. [5].

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About the author—ASKER M. BAZEN was born in The Netherlands in 1973. He received his M.Sc. degree in Electrical Engineering from the University of Twente in 1998 for his research on high-resolution parametric radar processing, which he continued for one more year at Thomson-CSF Signal. In September 2002, he has finished his Ph.D. thesis at the chair of Signals and Systems of the University of Twente on various topics in fingerprint recognition, including robust minutiae extraction from low-quality fingerprints, matching elastically deformed fingerprints and indexing large fingerprint databases. Other research interests include signal and image processing, pattern recognition, and computational intelligence.

About the author—SABIH H. GEREZ received his M.Sc. degree in Electrical Engineering and his Ph.D. degree in Applied Sciences from the University of Twente, The Netherlands, in 1984 and 1989, respectively. He has worked for the Department of Electrical Engineering of the University of Twente as an assistant researcher (in the period 1984–1989) and as an assistant professor (since 1990). Starting from 2001 he is combining his academic activities with a position at National Semiconductor, Design Center Hengelo, The Netherlands. His research and teaching interests include design automation, VLSI design, signal processing, and computational intelligence. He is the author of the book "Algorithms for VLSI Design Automation" (Wiley, 1999).