Fingerprint Matching Method Using Minutiae Clustering and Warping

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Abstract. Solving non-linear distortion problems in fingerprint matching is important and still remains as a challenging topic. We have developed a new fingerprint matching method to deal with non-linear distortion problems efficiently by clustering locally matched minutiae and warping the fingerprint surface using minutiae clusters. Specifically, local invariant structures encoding the neighborhood information of each minutia are utilized in clustering the matched minutiae and then the fingerprint surface is warped to describe the deformation pattern properly. Finally, to make an additional increase in performance, the overlapped region of two fingerprints is considered in the score computation stage. Experimental results show that the proposed algorithm is performed best compared with other ones.

I. Introduction

Fingerprint recognition is coming into the spotlight among the biometric technologies while having a very good balance of all the desirable properties: distinctiveness, permanence and performance etc [8]. In the last ten years there are great advances in the field of automatic fingerprint identification system (AFIS), and it is a matter of course that the most important stage of AFIS is the fingerprint matching. Although there are several fingerprint matching paradigms, we focus on minutia (ridge ending and ridge bifurcation) based approach which is known to the most popular and accurate method for the verification. For supporting compatibility to an ANSI/NIST standard [9], and also using already extracted minutiae templates of existing systems, it is required for a fingerprint matching system to use only location and orientation information of the minutiae. In this context, the fingerprint matching can be considered as a simple point pattern matching problem finding number of corresponding point pairs.

In general, there are several difficulties have to be considered in this simple problem. One is a possibility of spurious or dropped minutia from the minutiae extraction stage, usually this problem is caused by differences of user's skin condition as well as pressure and position changes to the fingerprint reader. Next problem is non-linear distortions due to non-uniform finger pressure and elastic characteristics of the skin. Any of fingerprint matching algorithms must deal with above problems for achieving a good performance.

Especially for the distortion problem, various methods have been developed in the literature. Jain et al. [5] use sampled ridge information and adjustable bounding box for finding corresponding pair. However it is not an efficient method for large deformation errors since they basically consider only the rigid transformation. Cappelli et al. [3] propose a mathematical deformation model for describing non-linear distortion. However, since this model relates non-distorted with distorted fingerprints, it is not appropriate to the purpose of fingerprint matching that usually needs a relation between two distorted fingerprints. Actually, the relation of two deformed surface is not simple to describe as a mathematical model. Bazen and Gerez [1] applied a thin-plate spline (TPS) model to deform fingerprints in an iterative manner. However, there are no appropriate constraints to control iterative warping procedures. Though their method significantly raises the scores of genuine matching, it raises the scores of imposter matching so the false matched rate. Recently, Ross et al. [12] propose ridge curve correspondences for fingerprint warping using TPS model. However their method needs training a deformation pattern for each specific person, and trained average deformation model is useless to large deformation cases.

In this paper, we present a new fingerprint matching method solving non-linear distortions. First of all, local neighborhood structures reliable to spurious as well as dropped minutiae are created for each of template (T) and input (I) fingerprints. The input fingerprint is aligned to the template fingerprint using this local structures. With transforming input fingerprint from aligned location iteratively, matched minutiae clusters are found. Then undistorted input fingerprint is obtained by warping input fingerprint using matching clusters as control points.

Finally, matching pairs are achieved using global matching strategy. For the score computation, an overlapped area between two bounding boxes of template and input fingerprint minutiae is considered in addition to a summation of similarities from matched minutiae pair. The proposed method is intuitively natural since clustering local matches and combining the information of these clusters resembles human expert's behavior. The rest of this paper is organized as follows: Section 2 describes the proposed matching algorithm. Section 3 shows experimental results. Finally, Section 4 draws some conclusions.

II. The matching algorithm

A flow chart of the proposed algorithm is described in Figure 1. In this section, we firstly explain the local neighborhood structure which is used in most algorithm stages. Next, we present detailed explanations of each functional part of the proposed method.

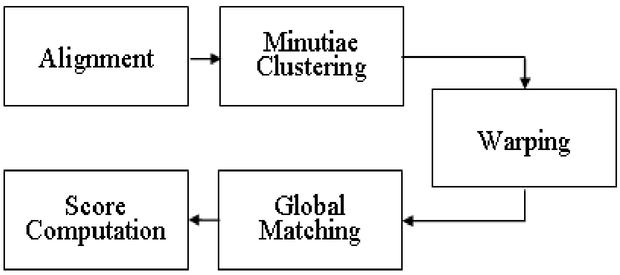


Figure 1. Flow chart of proposed algorithm.

1. Local neighborhood structure

We contrive a local neighborhood structure for each minutia, i.e. *k-directional nearest neighbor* (*k*-DNN). his structure is invariant under translation and rotation, and reliable on global deformation effects. The procedure of constructing the *k*-DNN as follows: Arrange local coordinate which makes the ridge orientation as x axis, divide the plane to be *k* slots, and find the nearest neighbor (NN) for each slot. One can avoid selecting spurious minutiae using minimum distance threshold for selecting NN, and also distortion invariant properties can be given by maximum distance threshold. For the k^{th} NN, we encode the angle and distance from the reference minutia and the orientation of NN as θ_k, d_k and φ_k, respectively. In Figure 2, a square (blue), round (red) and cross (green) headed line represent a reference minutia, a minutia selected NN for each slot and a remaining minutia around k-DNN structure, respectively. In the left of the figure one can see a *k*-DNN example, and right shows encoding parameters for the k^{th} NN. We empirically set $k=8$ for *k*-DNN in the experiment.

For examining the connectivity of *k*-DNN, all of the edges between reference and NN minutia are superimposed on real template and input fingerprint sample in Figure 4 (a) and (b) by blue and red color respectively.

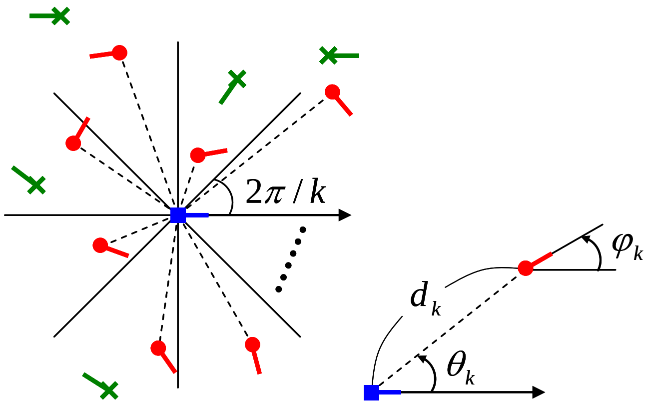


Figure 2. A *k*-DNN (left) and encoding parameters for the k^{th} NN (right).

2. Alignment

After constructing *k*-DNN structures for all minutiae of template and input fingerprints, alignment parameters is obtained by comparing these structures. For each *k*-DNN structure of template fingerprint, a similarity is compared with each of the *k*-DNN structures of input fingerprint. The similarity is computed by counting the number of the support NN which is determined by checking differences of each component of k^{th} NN. If the similarity is above the pre-defined threshold, transformation parameters and similarity for the current minutia correspondence are stored. The transformation is assumed to be the rigid transformation and one set of the translation and rotation parameters can be computed from one minutia correspondence pair by comparing location and orientation. After comparing all possible minutia pairs, we compute a total similarity for each stored parameter. The total similarity is calculated as summing up the similarities of stored elements which fall on the pre-defined bin sizes of reference transformation parameters. Final alignment parameters are determined by finding the element having the maximum total similarity. This local structure based alignment is significantly faster than Hough transformation based approach which searches the full parameter space [10].

An alignment example is shown in Figure 4 (c). In this figure, template and input minutiae represented as round (red) and square headed (blue) lines, respectively, and bounding boxes of template and input minutiae are drawn in rectangles.

3. Minutiae clustering

A minutiae clustering is the most important stage characterizing non-rigid transformation properties. If we transform input fingerprint freely to the template by rigid transformation, we can find several transformation parameters which collect matched minutiae to some region. In other words, there exist several matched minutiae clusters corresponding to some transformation parameters. Our clustering method is motivated on this observation.

We find one minutiae cluster at one iteration step. After aligning the input fingerprint to the template, we firstly find minutiae correspondences by applying pre-defined distance and angle bounds on the each template minutia location. By means of discarding a number of isolated matching which is detected by checking connectivity of *k*-DNN structure, we can obtain the largest number of matched minutiae clustered in some region. This first matched minutiae group is called as cluster 1. We observe that it is hard to find minutiae pairs in the distance from the cluster region because the deformation effect is accumulated in the outside direction. From the observation that the local structure similarities between template and input minutiae are also preserved at the unmatched region, the remaining unmatched minutiae is aligned to the appropriate position using the same method of previous section while neglecting the minutiae of previously matched region. Then an additional cluster is found by the same matching method as above and named as cluster k in sequential order. This alignment-matching process is iterated until there's no possible clustered region. During finding clusters, a minutia matching cost w ranging zero to unity is saved.

Figure 4 (d) shows an example of clustering minutia, where four clusters are obtained and represented in different colors. One can see all clusters are properly localized due to the rigorous connectivity check.

4. Warping

In the previous stage, we find clusters localized several regions of fingerprint surface. Because there are still remaining unmatched minutiae among cluster regions, more possible correspondences can be found by warping input fingerprint surface to the template using all matched pairs on clusters. We use thin-plate spline (TPS) to model the fingerprint surface warping. The TPS model is a popular tool which interpolates surfaces over given point correspondences and represents an analytic solution for minimizing bending energy of thin plates [2].

The fingerprint surface is interpolated exactly by following basic TPS equation [11],

$$\mathbf{Kw} + \mathbf{Pa} = \mathbf{v} \tag{1}$$

where $\mathbf{K}$ is basis function matrix, $\mathbf{w}$ defines an non-linear deformation, $\mathbf{a}$ gives affine part of transformation, $\mathbf{P}$ and $\mathbf{v}$ are input and template minutiae location matrices respectively. However exact interpolation can distort fingerprint surface erroneously by low reliable correspondences which have low minutia matching cost. To approximate the interpolation in vicinity of low reliable correspondences, we propose to use the weighted regularization method as follows,

$$(\mathbf{K} + \mathbf{\Lambda})\mathbf{w} + \mathbf{Pa} = \mathbf{v} \tag{2}$$

where $\mathbf{\Lambda} = diag(\lambda_1, \lambda_2, \ldots, \lambda_n)$ is regularization parameter matrix. Each λ_k defines a degree of surface smoothness at the k^{th} correspondence, which is calculated from the minutia matching cost. A warping example is showed in Figure 4 (e), the grid pattern represents undistorted surface of the input fingerprint. One can observe the locations of template and input minutiae are properly fitted.

5. Global matching and scoring

As the previous process warps the surface of input fingerprint to make similar shape of template one, smaller distance bounds than that of clustered matching is applied for finding matched minutiae in the global matching stage. However more angle difference is allowed as the minutiae orientation is not changed during warping. Though minutiae orientations can also be used for TPS warping [11], we do not use them from the fact that the edge is more erroneous than the corner. In addition, the isolated minutia checking is not applied for global matching.

For score computation, the following equation [1] is commonly used,

$$s(T, I) = \frac{{N_P}^2}{N_1 N_2} \tag{3}$$

where N_1 and N_2 are the numbers of template and input minutiae, respectively, and N_P means the number of matched minutiae. However, the similarity also depends on an overlapped region of aligned fingerprints, so (3) is not a reliable model. A new score computation method is proposed which considers an overlapped area of two bounding boxes of template and input fingerprint as following,

$$s(T, I) = \frac{A_O}{A_1}\left(\frac{S_P}{N_O}\right)^2 \tag{4}$$

where A_O and A_1 are area of overlapped and template minutia, respectively, $S_P = \sum_{i=1}^{N_P} w_i$

means the total minutia matching cost, and N_O is the number of minutiae in the overlapped region. In (4) the overall confidence level is limited by A_O / A_1, and for more robust measurements in the overlapped region N_P, $(N_1 N_2)$ in (3) are changed to S_P N_O^2, respectively.

In Figure 4 (f) final matching pairs are superimposed on the alignment configuration. The overlapped area of bounding boxes is represented as the colored region. One can see the input fingerprint is matched perfectly to the template.

III. Experimental results

The proposed algorithm has been evaluated using FVC2002 DB1_A database. The database consists of 800 fingerprint images with 100 distinct fingers and 8 impressions per finger. We performed a total of 2,800 and 4,950 comparisons for genuine and imposter matching, respectively, in accordance with the protocols of FVC2002 [7]. The evaluation parameters used in this results are referred to [6]. The comparative results of the proposed approach, two rigid matching methods and BOZORTH3 algorithm from NIST Fingerprint Image Software 2 [13] are presented in Table 1 and Figure 3. For the minutiae extraction, we use a binarization approach with fingerprint image enhancement method [5, 4]. The same minutiae extraction results are applied to all tested algorithms for comparing the performances of matchers only.

The rigid matching 2 uses the same functional parts as proposed approach without minutiae clustering and warping procedure. The rigid matching 1 uses the identical procedure with rigid matching 2 except using (3) for score computation. The BOZORTH3 algorithm implicitly allowing non-linear distortion effects during traversing the inter-fingerprint compatibility table, detailed description to be referred in [13].

The result shows the proposed approach is performed best among the all comparing algorithms, and BOZORTH3 algorithm performed worse than rigid matching 1 which is our most simple approach. By comparing rigid matching 1 and 2, we see that the better result is achieved using the proposed scoring method. An average matching time is 7.9 ms for genuine matching tests and 2.5 ms for imposer cases on an Intel Pentium 4, 3.4 GHz machine. The imposter test is usually faster than the genuine test since the number is matched minutiae is small and the count of cluster is below one in most cases, so the warping stage is passed.

Table 1. Results on FVC2002 DB1_A

Method	EER	FMR100	FMR1000
BOZORTH3	3.35%	5.25%	7.14%
Rigid matching 1	2.03%	2.43%	4.18%
Rigid matching 2	1.32%	1.39%	2.43%
Proposed	0.99%	1.00%	1.54%

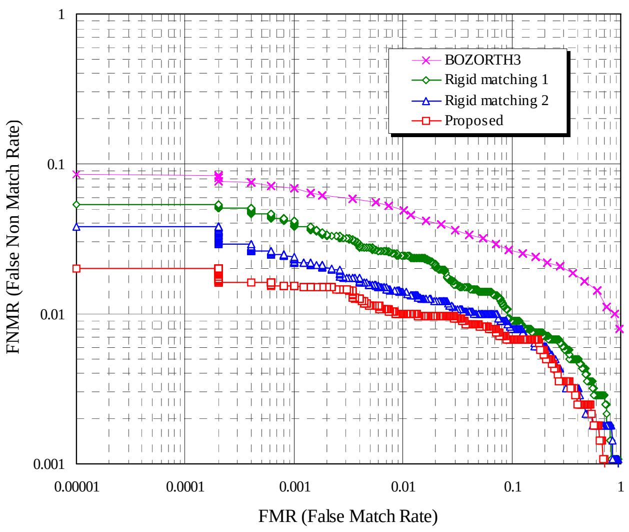
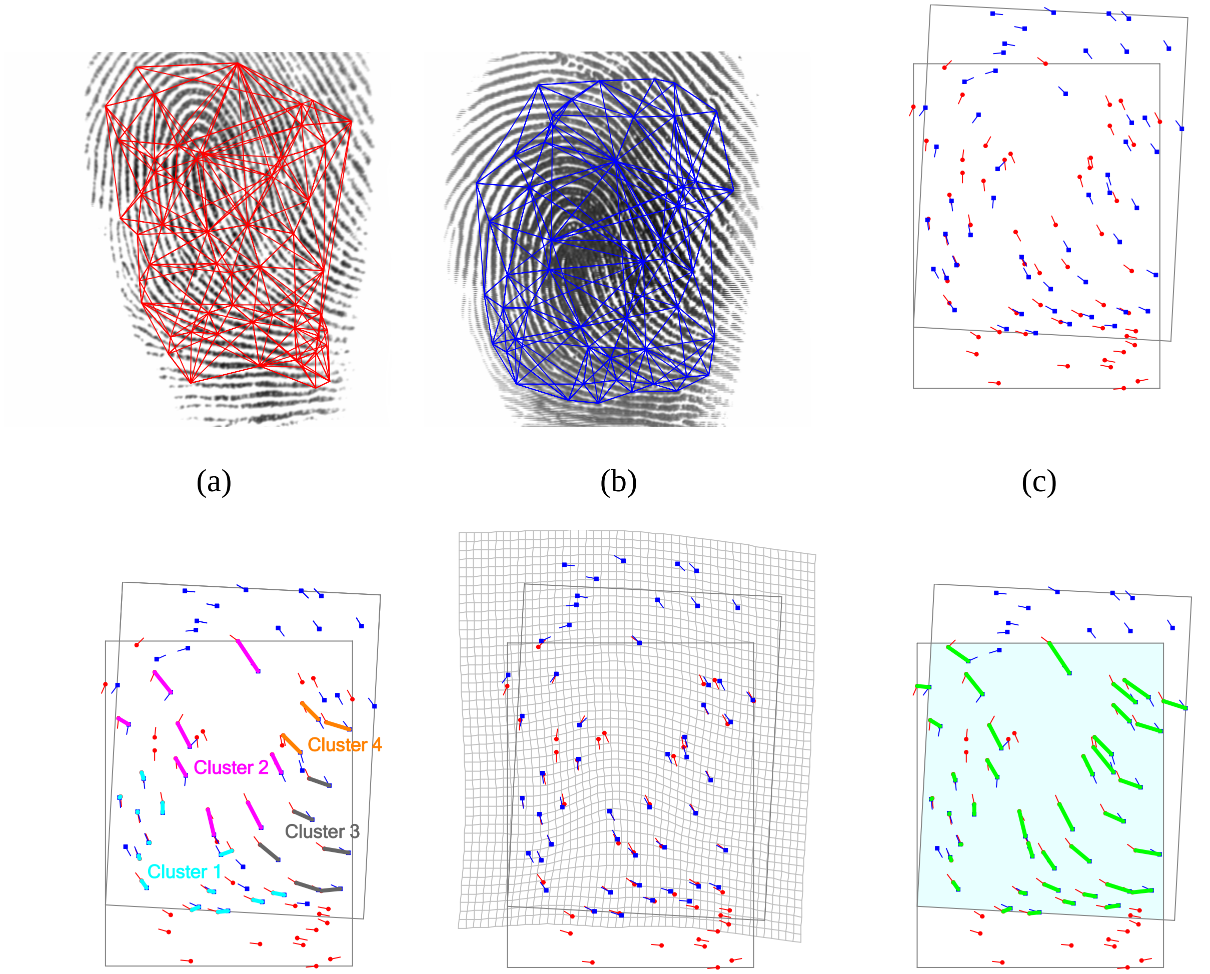


Figure 3. Comparative ROC curve.

IV. Conclusion

We have presented a new minutia-based fingerprint matching method that incorporates three new ideas. Firstly the new representation named *k*-DNN is defined to encode the local neighborhood of each minutia. Next, the clustered matching method is presented which finds local invariant structures the warping is used to describe entire surface deformation. Lastly the new score computation method is proposed which uses the overlapped region of two bounding boxes. We showed that the proposed algorithm performed better than rigid transformation based fingerprint matching methods as well as NIST BOZORTH3 algorithm in experimental results. The proposed score computation method provides substantial performance improvement.



(a) (b) (c)

(d) (e) (f)

Figure 4. An example of genuine matching between 78_1 (template) and 78_6 (input) from FVC2002 DB1_A (best viewed in color): (a) template fingerprint with collective NN edges of local neighborhood structures, (b) input fingerprint with collective NN edges of local neighborhood structures, (c) alignment result with bounding boxes, (d) minutiae clustering result (each cluster is colored differently), (e) warping result with grid pattern of input fingerprint surface, and (f) final correspondences with colored overlapped region.

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