Fingerprint Mosaicing Using Thin Plate Splines

S. Shah, A. Ross, J. Shah, S. Crihalmeanu
West Virginia University, Morgantown, WV 26506, USA
sshah@csee.wvu.edu, arun.ross@mail.wvu.edu, jidnyas@csee.wvu.edu, scrihalm@mix.wvu.edu

1. Introduction

We discuss a fingerprint mosaicing scheme to construct a composite fingerprint image using multiple impressions of the same finger. The composite image is expected to contain more information (e.g., minutiae) compared to the individual impressions thereby improving matching accuracy. The novelty of the proposed algorithm lies in its ability to account for the elastic deformation present in constituent fingerprints before stitching them. A 2D Thin Plate Spline (TPS) model based on minutiae correspondences between a pair of fingerprint images is used as the interpolant function to pre-distort one image based on its deformation with respect to the other. This aids in the better alignment of the two fingerprints and, consequently, better integration. Experiments conducted on the FVC 2002 DB1 database indicate that mosaicing results in a significant improvement in the matching performance.

2. Background

Various algorithms have been proposed for fingerprint mosaicing in the literature [2, 6]. Ratha et. al. introduced a method for constructing a rolled fingerprint from an image sequence of partial fingerprints using several blending algorithms [4]. Jain et al. used the iterative closest point algorithm to align and stitch fingerprint pairs [3]. Mosaicing is useful in the generation of a composite fingerprint image containing more information. However, most existing fingerprint mosaicing techniques do not explicitly model the elastic deformation present in constituent fingerprints. This type of deformation arises due to the elasticity of the skin as well as the pressure and movement of the finger during image acquisition [5]. In this work we employ the 2D Thin Plate Spline model to pre-distort a fingerprint image before mosaicing it with another impression.

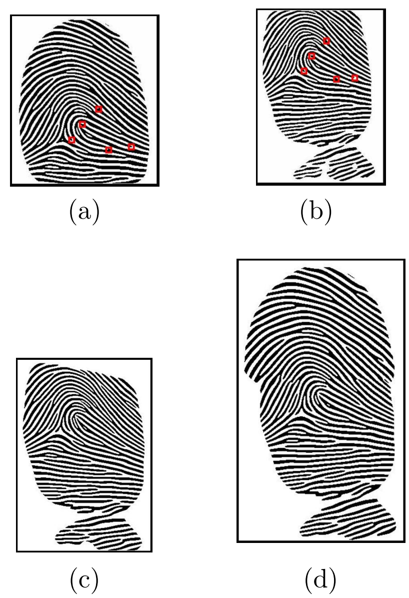

Figure 1. (a) Impression 1 (I_1), (b) Impression 2 (I_2'), (c) Deformation using TPS (I_2''), (d) The mosaiced image. The red points represent the landmark points used for determining the warping function.

3. Fingerprint Mosaicing using Thin Plate Splines:

Our mosaicing algorithm consists of three main steps. **1. Coarse Alignment:** Let I_1 and I_2 be 2 grayscale fingerprint impressions of a finger, and let T_1 and T_2 be the corresponding minutiae sets. In order to determine a coarse (affine) alignment between T_1 and T_2, the brute-force technique described in [5] is used. An arbitrarily selected reference minutia pair (one minutia from each set) is first used to estimate the translational and rotational offsets such that a large number of minutiae points in T_1 are paired with those in T_2. This exercise is repeated by considering all possible pairings of minutiae in the two sets, and finally reporting the transformation which results in the maximum number of matched minutiae. The image I_2 is then subjected to this affine transformation resulting in I_2'. **2. Fine Alignment using TPS:** This coarse alignment is not sufficient for registering two fingerprints due to the inherent elastic deformations introduced by the acquisition process. TPS, a 2D spatial generalization of the cubic spline, is an effective tool for estimating the deformation in fingerprints based on landmark points [1]. We use the brute-force minutiae matching technique discussed above to obtain a set of n matching minutiae pairs (landmark points), $M_1 = \{(x_{1,i}, y_{1,i})|i = 1, 2, \ldots n\}$ and $M_2 = \{(x_{2,i}, y_{2,i})|i = 1, 2, \ldots n\}$, from images I_1 and I'_2, respectively. The mapping function $f : R^2 \rightarrow R^2$ is defined as $f(x, y) = \sum_{i=1}^{n} w_i U(|(x_{1,i}, y_{1,i} - (x, y)|)$. Here w_i, $i = 1, 2...n$, is the 1×2 weight matrix, and $U(r) = r^2 log(r^2)$, r being the distance between pixel (x, y) and landmark point $(x_{1,i}, y_{1,i})$. This function uniquely minimizes the 'bending energy' required to warp I'_2, resulting in the deformed image I''_2. **3. Blending:** The region of overlap between I_1 and I''_2 is determined using the TPS function. A simple pixel averaging scheme is used to blend the images at the boundary. The composite image is then enhanced in order to obtain the mosaiced template (see Figure 1). A COTS software was used for minutiae extraction and image enhancement.

4. Experimental Results:

The performance of our mosaicing algorithm was tested on the FVC2002 DB1 database that has eight impressions each of 110 subjects. Two impressions of each subject (I_1 and I_2) were used as template images while the remaining 6 impressions were used as test images (Q). The composite image, C, for each user was generated using I_1 and I_2. Image pairs exhibiting large deformations resulted in incorrect minutiae correspondences thereby confounding the resultant TPS deformation model. In these instances (there were 18 of them), the composite image, C, was replaced by the individual impressions, I_1 and I_2, and the sum rule was used to fuse the match scores during the testing stage. The average number of minutiae in the composite fingerprints increased from 36 to 45 after mosaicing. Figure 2 shows ROC curves for five different matching scenarios: (a) I_1 with Q; (b) I_2 with Q; (c) combining match scores of (a) and (b) using the sum rule; (d) C with Q; and (e) C with Q excluding the 18 users indicated above. Matching was accomplished using a minutiae-based COTS matcher. The matching performance is observed to improve significantly when the composite template is used instead of the individual impressions. We also observe that fusion at the match score level gives the best performance. However, unlike mosaicing (image level fusion), score level fusion requires storing multiple templates per user in the database which also increases the time required for matching.

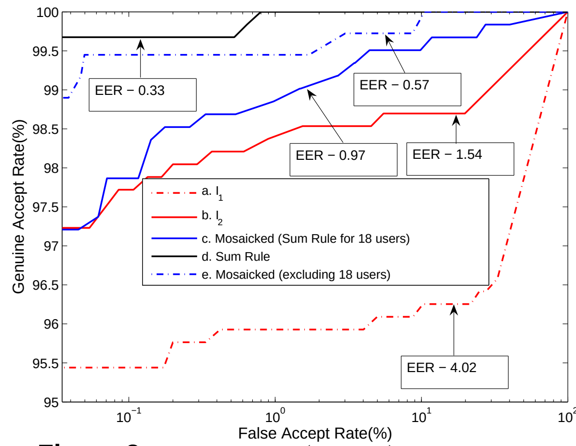

Figure 2. ROC curves (colored) indicating mosaicing performance.

5. Summary and Future Work:

We have described a novel approach for fingerprint mosaicing using TPS which accounts for the elastic deformation present in constituent fingerprints. The TPS model is sensitive to the number of landmark points and their spatial distribution. Future work involves designing a regularization technique for deciding the optimal number of minutiae required for estimating the TPS parameters, and studying how iterative refinement, as proposed by Bookstein [1], can be used to provide a robust estimate of the alignment. Furthermore, a technique to select the 'best' pair of images to perform mosaicing from a given set of impressions has to be developed.

References

[1] F. Bookstein. Principal warps: Thin plate splines and the decomposition of deformations. *IEEE Transactions on PAMI*, 11(6), 1989.

[2] K. Choi, H. Choi, and J. Kim. Fingerprint mosaicking by rolling and sliding. In *Proc. of Audio- and Video-based Biometric Person Authentication (AVBPA)*, pages 260–269, Rye Brook, NY, July 2005.

[3] A. Jain and A. Ross. Fingerprint mosaicking. In *Proc. of IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, volume 4, pages 4064–4067, Orlando, FL, May 2002.

[4] N. Ratha, J. Connell, and R. Bolle. Image mosaicing for rolled fingerprint construction. *14th International Conf on Pattern Recognition*, pages 1651–1653, 1998.

[5] A. Ross, S. Dass, and A. Jain. A deformable model for fingerprint matching. *Pattern Recognition*, 38(1):95–103, 2005.

[6] Y.-L. Zhang, J. Yang, and H. Wu. A hybrid swipe fingerprint mosaicing scheme. In *Proc. of Audio- and Video-based Biometric Person Authentication (AVBPA)*, pages 131–140, Rye Brook, NY, July 2005.