Coarse-to-fine image registration for sweep fingerprint sensors

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Abstract. For reconstructing sweep fingerprint sequences, we propose a coarse-to-fine image registration scheme, which first uses the block-matching method as the preregistration and then adopts the curvature-based elastic registration as a fine estimation of nonlinear distortions between two consecutive frames. With respect to two existing state-of-the-art approaches, the new scheme becomes more robust against distortions and therefore the reconstruction accuracy is improved. [DOI: 10.1117/1.2208587]

Subject terms: curvature; image registration; nonlinear distortions; sweep fingerprint sensor.

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1 Introduction

The sweep fingerprint sensor, with the size of a narrow stripe, scans an image sequence of frames during a relative motion between the sensor and the finger.[1] It is propagated due to its decreased area and cost, but requires the image sequence to be reliably reconstructed. In two existing state-of-the-art reconstruction methods,[2,3] nonlinear distortions are neglected and the only possible transformation between two consecutive frames is assumed to be a global translation. Therefore these methods lack robustness to the presence of distortions, and may yield seams and/or blurs in the reconstructed images.

To deal with distortions, two main approaches have been reported in the literature. One accounts for the problem with the help of some mechanical guidance (e.g., force sensors) built into the sensor packaging. Unfortunately, most of the commercial fingerprint sensors do not mount force sensors and are not able to capture images at a high rate. The other addresses distortions after image sequence acquisition. There are only a few methods for modeling fingerprint distortions.[4,5] One prominent method is using minutiae correspondences as landmarks, and creating a deformation model using thin-plate splines (TPS). However, the TPS model depends on the availability of a large number of minutiae in the overlap between two consecutive frames. A minimum of four correspondence pairs is necessary to model nonlinear distortions for the TPS model. Due to the nature of swipe design of sweep fingerprint sensors, there are very few minutiae correspondences between two consecutive frames. In these cases, the TPS model cannot be used.

Recently, a curvature-based elastic registration model has been proposed, which not only produces accurate and smooth solutions but also allows for an automatic rigid alignment.[6] Though affine linear transformations belong to the kernel of this regularizer, the iterations to obtain the pleasing result may be quite large. In this letter, a coarse-to-fine image registration scheme is proposed to register two consecutive frames of the sweep fingerprint sequence: the block-matching method is first used for a coarse estimation of translation displacement, and the curvature-based elastic registration is then adopted for a fine estimation of nonlinear distortions.

2 Block-Matching-Based Preregistration

Let F_i and F_{i+1} denote two consecutive frames of a sweep fingerprint sequence $F=\{F_i\}_{i=1,2,\ldots,M}$. Given that F_i and F_{i+1} differ only by a translation displacement $\mathbf{u}=(u_1,u_2)^T$, their overlap Ω satisfies:

$$F_i(\mathbf{x}-\mathbf{u}) = F_{i+1}(\mathbf{x}), \quad \mathbf{x}=(x_1,x_2)^T \in \Omega. \tag{1}$$

Thus, the minimum mean absolute error (MAE) between F_i and F_{i+1} for an $h_b \times w_b$ block $\mathcal{B}$ is:

$$\mathcal{M}(\mathbf{u}) = \frac{1}{h_b \times w_b}\sum_{\mathbf{x}\in\mathcal{B}} |F_i(\mathbf{x}-\mathbf{u}) - F_{i+1}(\mathbf{x})|. \tag{2}$$

Then the optimal translation displacement $\mathbf{u}'$ can be evaluated:

$$\mathbf{u}' = \arg\min_{\mathbf{u}} \mathcal{M}(\mathbf{u}). \tag{3}$$

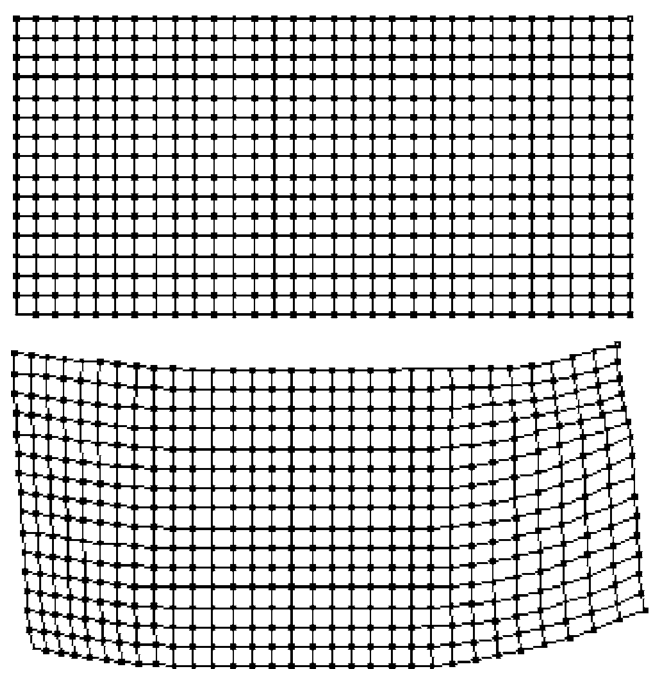

Fig. 1 The nonlinear distortions between two consecutive frames, one before and one after deformation.

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Fig. 2 Fingerprint reconstruction from a sweep sensor: some consecutive frames of a sweep fingerprint sequence and the reconstructed image.

3 Curvature-Based Elastic Registration

The curvature-based image registration can be summarized as follows: find a mapping $\mathbf{v}=(v_1,v_2)^T$, which minimizes the joint criterion

$$\mathcal{J}[\mathbf{v}] = \alpha\mathcal{S}[\mathbf{v}] + \mathcal{D}[F_i', F_{i+1};\mathbf{v}], \tag{4}$$

where

$$F_i'(\mathbf{x}) = F_i(\mathbf{x}-\mathbf{u}'),$$

$$\mathcal{D}[F_i', F_{i+1};\mathbf{v}] = \frac{1}{2}\int_\Omega [F_i'(\mathbf{x}-\mathbf{v}) - F_{i+1}(\mathbf{x})]^2\, d\mathbf{x},$$

$$\mathcal{S}[\mathbf{v}] = \frac{1}{2}\sum_{l=1}^{2}\int_\Omega (\Delta v_l)^2\, d\mathbf{x}.$$

Here, the regularization parameter α is used to control the strength of the smoothness $\mathcal{S}$ of the displacement versus the similarity $\mathcal{D}$ of two consecutive frames, and "Δ" is a Laplacian operator.

The Euler-Lagrange equation for Eq. (4) is

$$f[\mathbf{x},\mathbf{v}(\mathbf{x})] + \alpha\Delta^2\mathbf{v}(\mathbf{x}) = 0, \quad \mathbf{x}\in\Omega, \tag{5}$$

where $\mathbf{v}$ is subject to the boundary conditions

$$\nabla v_1 = \nabla v_2 = \nabla\Delta v_1 = \nabla\Delta v_2 = 0 \text{ on } \partial\Omega.$$

Here, $\partial\Omega$ is the boundary of Ω and "∇" is the spatial derivative operator.

The fourth-order nonlinear partial differential equation (PDE) of Eq. (5) is known as the biharmonic equation. A popular approach to solve this PDE is to introduce an artificial time t and to compute the steady state solution of the time dependent PDE. A semidiscrete time-marching method based on a real discrete cosine transformation is developed in Ref. 6, in which a finite difference approximation for the spatial derivatives is used. This leads to a linear system that can be efficiently solved within $\mathcal{O}(N\log N)$ operators and is adopted in our implementation.

Once two consecutive frames are registered, the reconstruction of a sweep fingerprint sequence is finished iteratively till the last frame F_M is mosaicked. Because the block-matching method using the MAE as a similarity measurement succeeds in registering two consecutive frames with small overlap down to 5% of the frame size[7] and the curvature-based elastic registration produces accurate and smooth solutions against nonlinear distortions,[6] better reconstruction accuracy is expected.

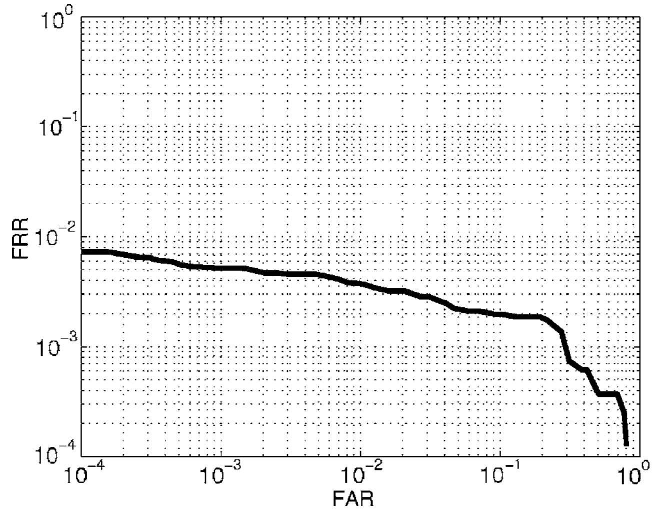

Fig. 3 ROC curve of the matching method embedded with the proposed coarse-to-fine registration scheme on our database.

4 Results

To evaluate the proposed registration scheme for the reconstruction, we need a database including a considerable number of sweep fingerprint sequences. Such a database is, however, not available in standard fingerprint databases (e.g., FVC2000). Therefore, we have acquired sweep fingerprint sequences of 180 fingers using a Fingerprint Cards' FPC1031B sweep sensor (each frame with 152 $\times$32 pixels, and 363 dpi) over a period of 4 weeks. For each finger, 10 sequences have been acquired, producing a total of 1800 sequences. In Fig. 1, the grid is used to visualize the nonlinear distortions between two consecutive frames, which can be viewed as two different observations of an elastic body, one before and one after a deformation. In Fig. 2, some consecutive frames of a sweep fingerprint sequence and the reconstructed image are illustrated. To be precise, we have chosen for our scheme the parameters h_b $=2$, $w_b=110$, and $\alpha=100$. In order to compare the recognition performance with existing reconstruction methods,[2,3] a straightforward method has been implemented, consisting of minutiae extraction and minutiae matching, on the reconstructed fingerprint images.[8] The following indices are used to assess the recognition accuracy: (1) equal-error rate (EER), which denotes the error rate when the false acceptance rate (FAR) and the False Reject Rate (FRR) are identical; (2) receiver operating characteristic (ROC) curve, which plots the FRR against FAR at various matching thresholds. The ROC curve for the elastic matching embedded with the proposed reconstruction scheme is shown in Fig. 3 and the corresponding EER is 0.46%. Meanwhile, the EERs corresponding to the reconstruction methods proposed in Refs. 2 and 3 are 0.84% and 0.92%, respectively. It is seen that the proposed coarse-to-fine registration scheme leads to a better recognition performance than the other two.

5 Conclusions

The reconstruction algorithm plays a vital role in image quality for the sweep fingerprint sensor. Due to the elasticity of the skin, nonlinear distortions are the most difficult problem during the reconstruction. In this letter, we propose a coarse-to-fine image registration scheme for reconstructing the sweep fingerprint sequence: a curvature-based elastic registration model is adopted to address nonlinear distortions after the block-matching method is used to estimate the translational displacement. Experiments show that the proposed scheme is more robust against nonlinear distortions than the two existing state-of-the-art methods. Therefore the reconstruction accuracy is improved. Our aim in this letter is to boost the application of the sweep fingerprint sensor in embedded systems or mobile devices.

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