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Registration for Frameless Brain Surgery Based on Stereo Imaging*

Yau-Zen Chang, *Senior Member, IEEE,* and Jung-Fu Hou

Abstract—**This paper presents an implementation of stereo vision techniques to capture the geometric model of patient's face for registration in the frameless neurosurgery. A distance transform is applied on 2D CT/MRI multi-slices for on-site registration, further reducing requisite computation. In order to validate accuracy of the system, we designed a phantom to directly measure its target registration error (TRE). Experimental results show that the TRE is 2.72 ± 0.735 mm.**

I. Introduction

Surface matching [1], especially the registration between human face feature and CT/MRI image, has been an important approach to reference patients to a navigation system for frameless neurosurgery. The approach completely replaces stereotactic frames, bone-implanted fiduciary marker or skin-attached markers for registration.

There has been many ways to obtain the face contour in the physical space, either by direct contact or remote sensing, such as laser range scanner [2-3] and optical [4] or electrical magnetic [5] positioning devices. However, sensing the skin via direct contact suffers from elasticity of the skin, while hand-held registration using laser reflections [6] relies on steadiness of the operator to collect well-distributed data on interested regions. Based on recent advances in image technology, we have developed procedures for the dual-camera calibration [7] and reliable scheme [8] for 3D modeling of human face using a dual-camera system.

Besides, the huge size of the extracted point clouds of 3D shapes demands an efficient algorithm to register these two datasets. Among the methods to register CT/MR images with 3D face data, the Iterative Closest Point (ICP) algorithm [9], together with building a k-D tree [10], has been the dominant method. Although these approaches are fast enough for practical applications, however, they are extremely sensitive to initial pose and require multiple trials to find a reliable solution.

To alleviate this shortage with comparable speed, we propose a Chamfer Distance Transform method [11] to assign distance quantities at each CT image layer.

With this transform, degree of match can be directly estimated by direct indexing without calculation of distances between closest points. Major improvement in performance of the approach comes from the benefit that the distance transform has to be executed only once for the layers.

In order to validate accuracy of the system, we designed and made a phantom using the iPro 8000 SLA Center, 3D Systems Inc. [12]. Inside the phantom, there are accurately allocated markers for direct estimation of the target registration error (TRE) [13].

II. Method

A. *The overall framework*

The proposed neurosurgical navigation system employs stereovision to capture 3D facial data. By registering CT/MR imaging with the geometric face data, medical 3D images are aligned with the patient in the physical space for further treatment, such as image-guided surgery (IGS) or medical augmented reality (AR).

The stereo vision system is built using two Sony D-70 PTZ cameras, which requires only one pair of shots for 3D modeling. 3D Coordinates of the points representing human face is derived from corresponding locations on images captured from the same scene. In [8], we proposed a scheme which requires only one exposure to find the correspondence between intensive locations in the images for 3D reconstruction. The method is initiated with the SIFT algorithm [14], and successive correspondences are found in order using an optimization algorithm.

For direct registration between CT/MR imaging and 3D face data, the surface contours are extracted from CT slices, and the optimization algorithm is used to find the best coordinate transformation for the face data to match that of the corresponding surface points in the CT images. We propose a Chamfer Distance Transform [11] to assign distance quantities at each CT image layer for estimating the degree of match used in the optimization algorithm.

Both the problems of searching matching locations in 3D facial model construction and registration between CT/MR imaging and 3D face data can be transformed into minimization tasks and solved by efficient optimization methods. In [8], we proposed a parallel version of the Particle Swarm Optimization algorithm, denoted as the PPSO algorithm, for these tasks. The overall framework is illustrated in the flowchart of Fig. 1.

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Yau-Zen Chang and Jung-Fu Hou are with Chang Gung University, Taoyuan 33375, Taiwan (+886-3-2118800 EXT 5341, 5879; fax: +886-3-2118050; e-mail: zen@mail.cgu.edu.tw; frid.hou@gmail.com).

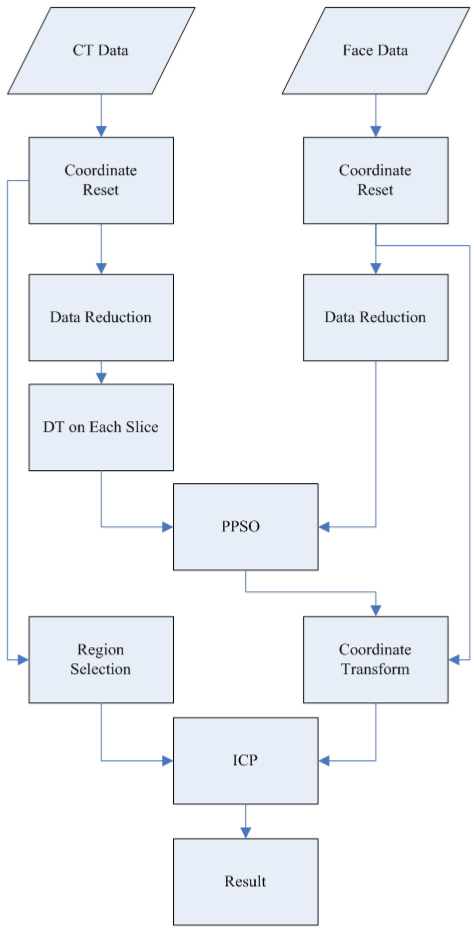


Figure 1. The flowchart of the registration between CT model and the reconstructed face data for the neurosurgical navigation system

B. Registration of CT Images and 3D Face Data Using Chamfer Distance Transform and Optimization Algorithm

Before In this section, we propose a robust procedure for registration of 3-D face data to the CT/MRI images without particular restriction on initial pose of the registered objects. Our approach includes application of the Chamfer Distance Transform [11] to assign distance quantities at each CT/MR image slice and the use of the PPSO optimization algorithm [14] to find the best coordinate transformation for the face data to match that of the corresponding surface points in the slices.

The computation of a two dimensional chamfer DT consists of the convolutions of two masks, the forward mask and the backward mask, with the binary image, as shown in Fig. 2. In the simplest form, both masks have only two rows: the forward mask is composed of [*b*, *a*, *b*], and [*a*, 1], and the backward mask [1, *a*] and [*b*, *a*, *b*], where *a* and *b* are design parameters related to gradient of distance. The convolution for the forward mask is row-wise down, from left to right, while the convolution for the backward mask is row-wise up, from right to left. If the pixel at (*i*, *j*) is with intensity $v_{i,j}$, the convolutions will result in

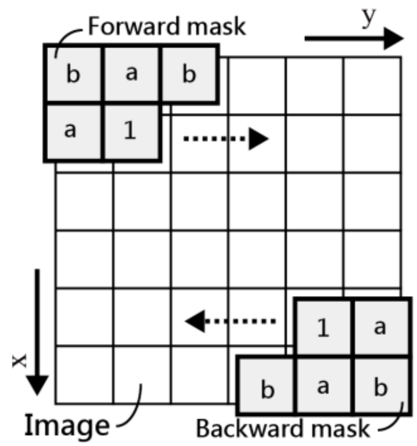


Figure 2. The forward mask and the backward mask in a two dimensional chamfer DT.

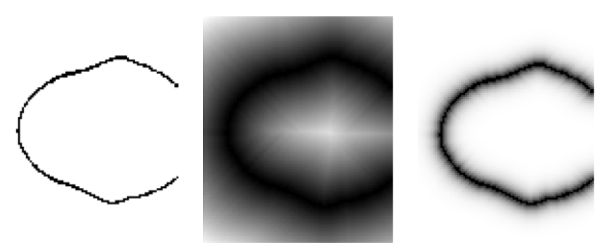
$$d_{i,j} = \min(v_{i-1,j-1} + b, v_{i-1,j} + a, v_{i-1,j} + b, v_{i,j+1} + a) \tag{8}$$

where $d_{i,j}$ is the intensity of the pixel on the distance map.

Figure 3(b) illustrates the distance map of a contour on a 113-by-95 pixels image, shown in Fig. 3(a), using mask parameters $a = 4$ and $b = 5$. In the distance map, the intensity of a pixel depends on its distance from the nearest pixel of the object. Note that the intensity at the pixels describing the object is 0 since the distance of a pixel from itself is zero. Further operations on the distance map may adjust the effects of distance. For instance, let $d_{i,j}$ be the intensity of a pixel on the i-th row and j-th column of a distance map, an operation of

$$d_{i,j}^{New} = 1 - e^{-0.1 d_{i,j}} \tag{4}$$

results in a modified distance map shown in Fig. 8(c), in which the dominating effect of the contour is significantly reduced. Figure 4 illustrates an overview of the resultant image slices.



(a) (b) (c)

Figure 3. (a) An illustrative simple object. (b) Distance map of the object using masks with a = 4 and b = 5. (c) Modified distance map using equation (4) to reduce the distance effect.

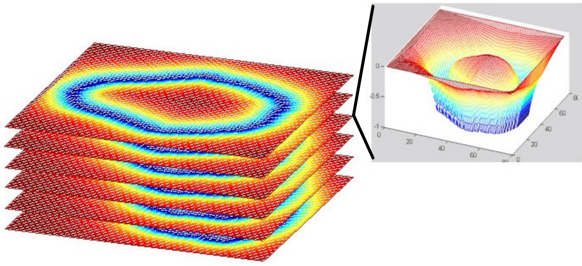


Figure 4. The application of distance map on each slide of the CT/MR images.

The degree of match, denoted as D, between two 2D images M and H, where M is a distance map similar to Fig. 8(c) and H is composed of data describing a contour similar to Fig. 8(a), can be defined as

$$D = \sum_{i}\sum_{j} d_{ij}^{M} \cdot (1 - d_{ij}^{H}), \tag{5}$$

where d_{ij}^{M} and d_{ij}^{H} are the intensity of a pixel on the i-th row and j-th column of images M and H, respectively. Since only d_{ij}^{M}'s are in grayscale, the calculation of the degree of match can be simplified by treating d_{ij}^{H} as a mask and summarizing the corresponding d_{ij}^{M}'s only.

For this registration case, M is a CT/MR image slice and H is a set of data points collected from the surface model of a patient's face on a particular cross section taking a trial orientation.

As shown in Fig. 5, the CT/MR image slices are discretely distributed in space with a constant distance of Δz, which is 0.8 mm in this example. In order to obtain d_{ij}^{H} of equation (5), 2D projections of the 3D data set of a patient's facial geometric model can be conducted by classifying the set into closest slices. Taking the numbered data points in Fig. 5 as an example, point 1 belongs to the surface of slide *a*, point 2 and 3 belongs to the surface of slide *b*, point 4 and 5 belongs to the surface of slide *c*, while point 6 belongs to the surface of slide *d*.

In the proposed registration procedure, the CT/MR image slices, the M images, are kept fixed, while the surface model of a patient's face, which provides the H images, is under rigid body transformation. This transformation is a combination of translation and rotation, and can be represented as a 4-by-4 homogeneous transformation matrix [16] when the data points are represented in homogeneous coordinates:

$$T(\theta) \quad \gamma, \Delta x, \Delta y, \Delta z)$$
$$= \begin{bmatrix} \cos\alpha\cos\beta & \sin\gamma\sin\beta\cos\alpha - \cos\lambda\sin\alpha & \cos\alpha\sin\beta\cos\gamma + \sin\alpha\sin\gamma & \Delta x \\ \cos\beta\sin\alpha & \sin\gamma\sin\beta\sin\alpha + \cos\alpha\cos\gamma & \cos\gamma\sin\beta\sin\alpha - \sin\alpha\sin\gamma & \Delta y \\ -\sin\beta & \sin\gamma\cos\beta & \cos\gamma\cos\beta & \Delta z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

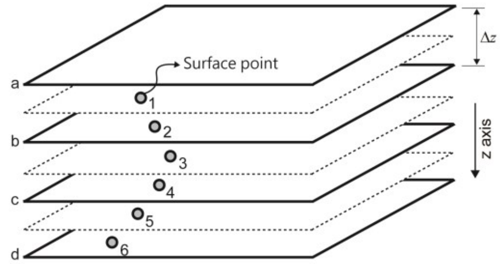


Figure 5. The relationship between CT/MR image slices and 3D data points of a patient's facial geometric model.

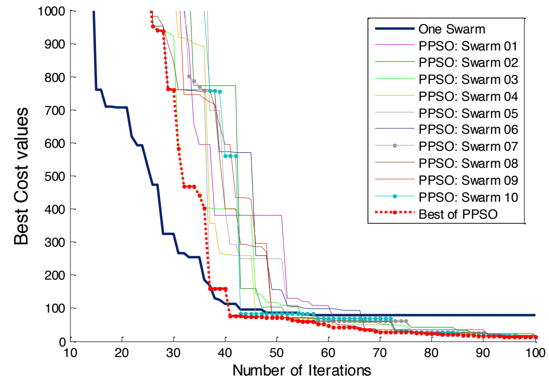


Figure 6. Convergence history of the best cost values in an implementation of 10 parallel swarms and one swarm.

where $\theta = [\alpha, \beta, \gamma, \Delta x, \Delta y, \Delta z]^{T}$ is the transformation parameter vector composed of Euler angles $\{\alpha, \beta, \gamma\}$ and the amount of translation $\{\Delta x, \Delta y, \Delta z\}$.

The degree of match, defined in (5), is a function of the transformation parameter vector, $D = D(\theta)$. The problem is then formulated into an optimization problem of searching for θ such that D is minimized. Figure 6 shows a typical comparison between the PPSO algorithm and the standard Particle Swarm Optimization algorithm, demonstrating the superiority of the algorithm.

C. *Accuracy validation*

A plastic CT-compatible phantom was made using the iPro 8000 SLA Center, 3D Systems Inc., for accuracy assessment. As shown in Fig. 7, the phantom has 24 artificial targets located on the head surface and 35 inside the skull; all are accurately designed using the Pro/ENGINEER Wildfire 5.0. The targets are 10 mm in diameter and 2 mm high with 1.5 mm wide pinholes at the center.

The registration accuracy was validated by on-site surface registration. The target registration error (TRE) is defined as the deviation between the coordinates estimated by the system and the CAD data. Experimental results show that the TRE is 2.72 ± 0.735 mm. Figure 8 shows the distribution of TRE of these 25 tested locations.

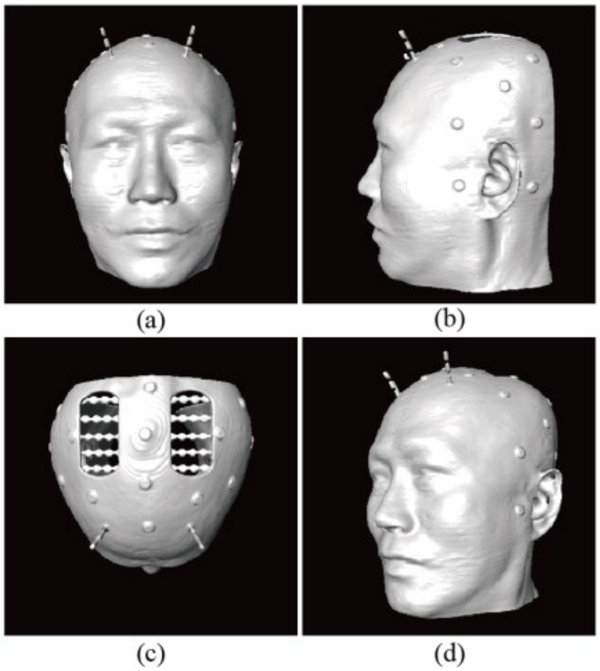


Figure 7. The CAD model modified from CT image of a person for phantom generation.

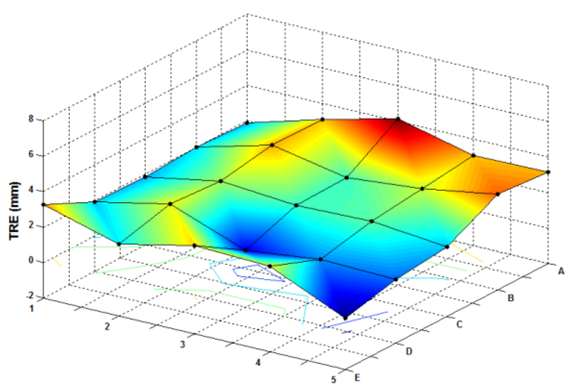


Figure 8. The distribution of the target registration error (TRE) of the 25 measured points.

III. Conclusion

This paper proposed an efficient registration strategy for frameless neurosurgery based on 3D human face data captured by a stereovision system. The registration between CT/MR imaging and the geometric face data allows medical 3D images to be aligned with the patient in the physical space for further treatment, such as image-guided surgery (IGS) or medical augmented reality (AR).

With the Chamfer Distance transform, degree of match can be directly estimated by indexing without calculation of distances between closest points. Major improvement in performance of the approach comes from the benefit that the distance transform has to be executed only once for the layers. Based on a practical registration procedure using a plastic phantom with 25 inside markers, the target registration error (TRE) is 2.72 ± 0.735 mm.

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