Anatomy-based Registration for Computer-integrated Surgery

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Abstract. In Computed-integrated Surgery (CIS), the registration between pre- or intra-operative images, anatomical models and guiding systems such as robots or passive systems is a crucial step. In our methodology, rigid or elastic transformations are estimated using non-linear least-squares minimization of euclidean distances computed on data that can be 3D surfaces or 2D projections. This paper shows the variety of results that is achieved with this framework on several clinical applications.

1 Introduction

In Computer-integrated Surgery (CIS) , the registration of the whole information available for a given patient is an essential step [TLBM95]. See [Lav95] for a review of standard methods. Several kinds of data may have to be registered :

- *Pre-operative data:* medical images such as CT, MRI, TEP, SPECT, ... or models, such as brain atlases (usually the basis for the surgical planning).
- *Intra-operative data:* medical images provided by low-cost systems (X-rays, echography, microscopes or endoscopes), or positioning information provided by various sensors (optical, ultrasonic, mechanical, or electro-magnetic 3D localizers, range imaging systems). Guiding systems that can be passive 3D localizers or active robots have also to be registered with the images on which the surgical planning has been defined and updated. For that purpose, the guiding systems have often to be calibrated with intra-operative sensors, which are in turn registered with the whole information.
- *Post-operative data:* similar to pre-operative data. They have to be registered to measure the efficiency of an intervention and to update the models.

A typical application will have to register pre-operative CT images with a 3D passive or active manipulator during surgery [LST+94]. In most of standard registration techniques used in CIS, material structures such as reference pins or balls have to be fixed to the patient. For several years, our group has been working on the concept of anatomy-based registration, according to which some reference anatomical structures of the patient provide sufficient features for registration. See [Lav95, LSB95] for a description of our methodology.

2 Registration method

In this section, we briefly present the algorithms that enable us to register a 3D surface model S with various sensor data. For all these algorithms, it is necessary to precompute and store a 3D distance map associated with the 3D surface model S. This distance map is a function that gives an approximation of the minimum signed euclidean distance $\tilde{d}$ to the 3D surface model S from any point $\mathbf{q}$ inside a bounding volume V that encloses S. This signed distance function is positive for a point located outside the surface S and negative for a point located inside it. Therefore, the zero of the 3D distance function gives a unique implicit representation of S. The distance map that we use is built from just a collection of 3-D points lying on the surface S and it is represented by an octree-spline which is a 3D adaptive and continuous distance map whose resolution increases near the surface, see [LSB91] for more details.

Rigid 3D-3D registration algorithm

In most of applications, the 3D model is the result of a segmentation procedure applied to MRI or CT images of a reference structure and sensor data can be represented by a collection of 3D points obtained through segmentation of a second series of 3D images (CT, MRI,...), through manual digitization of surface points (e.g., using an optical pointer), through 2.5D ultrasound image segmentation, or through range image acquisition.

In this case we look for the rigid transformation $\mathbf{T}(\mathbf{p})$, that depends on a 6-components vector $\mathbf{p}$ (3 translation components and 3 Euler angles), between the surface S known in $\mathrm{Ref}_{3\mathrm{D}}$ and a set of M_P points $\mathbf{q}_i$ known in $\mathrm{Ref}_{\mathrm{sensor}}$ (we make the assumption that most of the points $\mathbf{q}_i$ match to the surface). We look for the parameters $\mathbf{p}$ that minimize an error function given by the sum of squares of distances between the surface S and the 3D sensor points transformed by $\mathbf{T}(\mathbf{p})$ in the 3D reference system. The criterion to minimize is:

$$E(\mathbf{p}) = \sum_{i=1}^{M_P} \frac{1}{\sigma_i^2}[e_i(\mathbf{p})]^2 = \sum_{i=1}^{M_P} \frac{1}{\sigma_i^2}[\tilde{d}(\mathbf{T}(\mathbf{p})\,\mathbf{q}_i, S)]^2. \quad (1)$$

where $\tilde{d}(\mathbf{T}(\mathbf{p})\,\mathbf{q}_i, S)$ is the minimum signed distance between the surface S and the data point $\mathbf{q}_i$ transformed by $\mathbf{T}(\mathbf{p})$ in the 3D reference system. σ_i^2 is the variance of the noise of the measurement $e_i(\mathbf{p})$. The minimization of the error function is performed using the Levenberg-Marquardt algorithm [PFTV92]. Robust estimation is also performed by simply removing the outliers exceeding a given threshold and starting again new series of iterations.

Rigid 3D-2D registration algorithm

Sensor data may be also 2D X-ray or video projection images that have to be registered with a 3D surface model [LS95]. To perform such 3D-2D registration, the first step is to use the result of sensor calibration to calculate in $\mathrm{Ref}_{\mathrm{sensor}}$ the projection lines L_i associated with some pixels P_i that lie on the external contour of the projections of the reference structure. We then use a least-squares formulation similar to the previous one, except that the criterion (1) is now replaced by:

$$E(\mathbf{p}) = \sum_{i=1}^{M_P} \frac{1}{\sigma_i^2} [\tilde{d}_l(l_i(\mathbf{p}), S)]^2, \tag{2}$$

where $\tilde{d}_l(l_i(\mathbf{p}), S)$ is the minimum, along the projection line $l_i(\mathbf{p})$, of the distance, computed in the octree-spline distance map, to the surface S. $l_i(\mathbf{p})$ is the result of transformation $\mathbf{T}(\mathbf{p})$ applied to the projection line L_i.

Non-rigid 3D-3D registration algorithm

The data can also correspond to a structure slightly different from the model (e.g., registration of a patient's brain with an Atlas, or tracking of deformations). For such non-rigid registration, we extend the rigid 3d-3d registration algorithm by a significant modification of the transformation $\mathbf{T}$. Instead of 6 parameters, we have now hundreds of parameters $\mathbf{p}$ that describe the transformation between Ref_{3D} and $\mathrm{Ref}_{\mathrm{sensor}}$. Although we match surfaces, we represent the deformation as a volumetric transformation, that is represented by a second octree-spline. The coarsest level of the deformation encodes the global (e.g., affine) transformation between the two surfaces, while finer levels encode smooth local displacements which bring the two surfaces into closer registration. A 3D displacement vector is associated with each corner of each cube of the octree-spline built on the 3-D data points. The xyz coordinates of all these vectors constitute the parameters we are looking for. For any point $\mathbf{q}_i$ in $\mathrm{Ref}_{\mathrm{sensor}}$, the transformed point $\mathbf{r}_i = \mathbf{T}(\mathbf{q}_i; \mathbf{p})$ is computed in Ref_{3D} by interpolating the displacement vectors located at the corners neighboring the point $\mathbf{q}_i$. Therefore, the parameters $\mathbf{p}$ can be seen as the coefficients of an adaptative 3-D spline. The energy that we minimize in this problem is given by :

$$E(\mathbf{p}) = \sum_{i=1}^{N} \frac{1}{\sigma_i^2} [d(\mathbf{r}_i, S)]^2 + \mathcal{R}_m(\mathbf{p}), \tag{3}$$

where $d(\mathbf{r}_i, S) = d(\mathbf{T}(\mathbf{q}_i; \mathbf{p}), S)$ is the minimum Euclidean distance from the point $\mathbf{r}_i$ to the model surface S. Compared to equation (1), we have added a regularization term $\mathcal{R}_m(\mathbf{p})$ that makes the problem well posed (the solution is unique). This term is a combination of 0th and 1st order stabilizers that tend to minimize and smooth the amount of deformations. The minimization of this energy is much more complex than the previous one, and the use of the Levenberg-Marquardt algorithm now requires to solve a very large sparse system. Therefore, we have chosen to use a single step of preconditioned conjugate gradient descent using also hierarchical basis preconditioning techniques to make this process converge faster [SL94].

3 Results of registration algorithms in various clinical cases

MRI-CT registration using 3D scalp surface

In this application the scalp surface of a patient has been segmented on both MRI and CT images . The 3D-3D registration algorithm is applied on these two surfaces. The convergence takes only one second on a DEC-alpha workstation. Once this registration has been performed, for each MR image, the corresponding resliced CT image is computed and superimposed as we can see on Fig. 1.

The application of the same algorithm for SPECT/MRI registration using an intermediary Range Imaging Sensor is also presented in [PLC+93].

Registration using a manual digitization of surface points.

Using an optical 3D localizer makes it possible and easy to collect a set of surface points manually. For example, during an operation on spine, a surgeon can acquire some surface points lying on the posterior part of the vertebra. These points are registered with a CT surface model of the same vertebra. The overall accuracy is better than 1mm. This technique helps the surgeon drill a trajectory which has been defined on pre-operative CT images. Fig 2 shows the algorithm convergence between 3D surface points of a vertebra and the 3D surface model of this vertebra. This technique has been applied for open spine surgery on 6 patients [LST+94].

Registration using an ultrasound probe (2.5D ultrasound pointer)

It is also possible to replace a simple 3D digitizing probe by an ultrasound probe to acquire 3D data points during an operation. The idea is to measure the position of the ultrasound probe in space by adding a sensor on top of a standard ultrasound probe. On each image, some points that lie on the edge of a reference structure such as a bone are segmented, and this process is repeated for several images. The result is a set of 3D points in Ref_{sensor}, arranged in pieces of planar curves. The whole system that encompasses the ultrasound image digitization and segmentation is named *2.5D ultrasound pointer*. Such data can be registered with a 3D surface model as in previous examples. This technique has been successfully used for percutaneous spine surgery [BTML93] and for patient positionning in external radiotherapy [TMB+94] (see Fig. 3).

Registration of a 3D Surface with 2D projections.

The technique of 3D/2D registration has been tested on vertebra and skull surfaces interactively segmented on a pair of calibrated X-rays and semi-automatically segmented on CT data. Independant error measurements were obtained for both cases: less than 1mm for the vertebra, 2mm for the skull. This method has been technically validated for percutaneous spine surgery [SCLT92]. Fig. 4 shows the results obtained on a skull.

3D-3D elastic registration between two faces

To demonstrate the local non-rigid matching, we use two different sets of range data acquired with a Cyberware laser range scanner. In their initial positions, the data sets overlap by about 50% and differ in orientation by about 10° (Fig. 5a). Here, the octree spline distance map is computed on the larger of the two data sets (`george1`), and the smaller of the two data sets is deformed (`heidi`). After 8 iterations of rigid matching and 8 iterations of non-rigid affine matching, the registered data sets appear as in Fig. 5b. We then perform 8 iterations at each level of the local displacement spline for 1 through 5 levels. The octree spline has a total of 5728 cubes for a total of about 17000 degrees of freedom. Even with our large number of parameters, the algorithm converges very quickly, because it is always in the vicinity of a good solution (a typical iteration at the finest level takes about 2 seconds). From Fig. 5c, we see that the two data sets are registered well, except for the eyebrows.

4 Conclusions

In this paper, we have presented the application of quite simple registration techniques that we developed in the past five years for the domain of Computer-integrated Surgery. We have shown on real examples that a methodology based on distance minimization between anatomical reference structures can be used efficiently with many different types of data (3D images, range images, 3D points digitized manually, 3D points extracted on 2.5D ultrasound images, X-ray projections, models). All the results presented in this paper were obtained in a few seconds on DEC-Alpha workstations. The accuracy required for the specific applications was obtained in all cases.

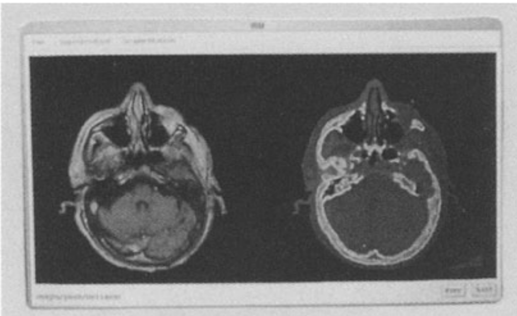

Fig. 1. superimposition of MRI and resliced CT images after rigid 3D-3D registration using the scalp surface. The result is visually perfect.

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Fig. 2. Rigid 3-D / 3-D registration: during spine surgery, a set of surface points acquired manually with an optical 3D localizer converges towards the 3-D model of the vertebra segmented on pre-operative CT images.

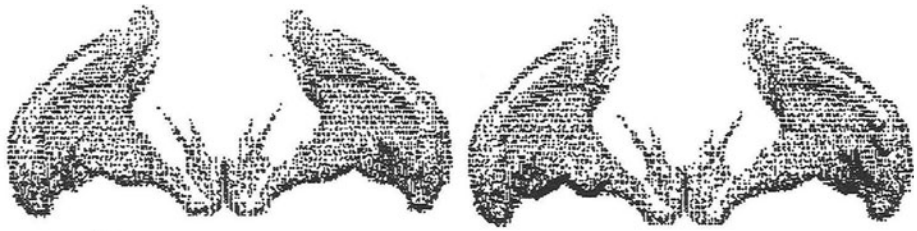

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Fig. 3. Rigid 3-D / 3-D registration : during an operation, 3D data points are acquired with a 2.5D ultrasound pointer and they are registered with a 3D model of the pelvis bone segmented on CT images. This method gives a millimetric accuracy.

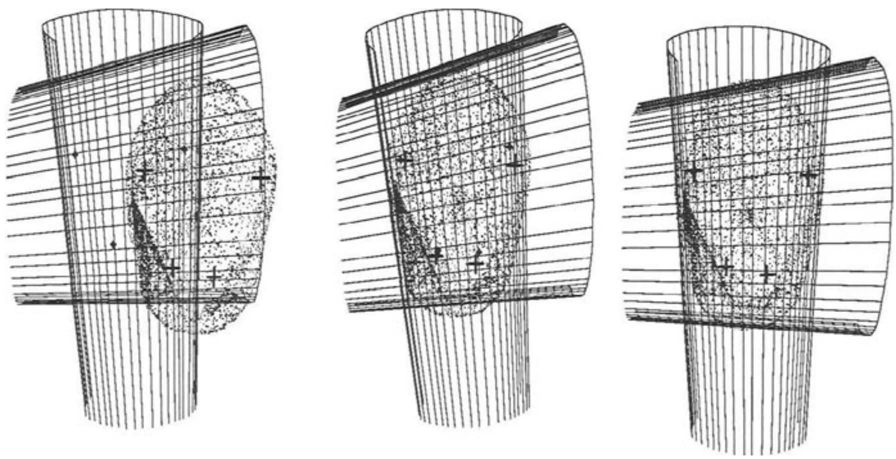

Fig. 4. Convergence of 3-D / 2-D algorithm : A set of projection lines issued from a pair of X-rays of the skull converges towards the skull surface segmented on CT images.

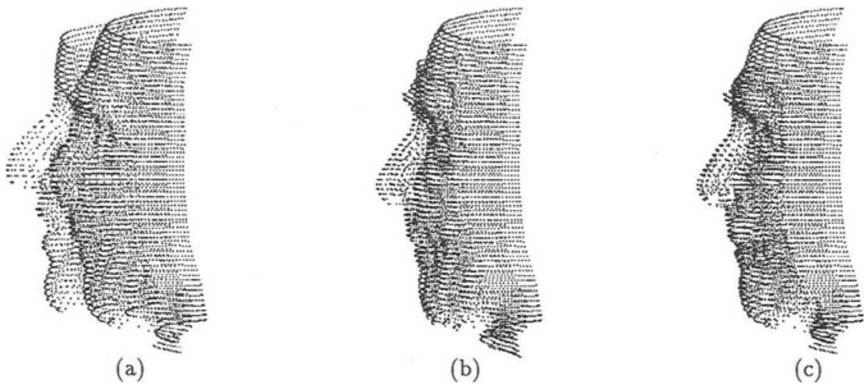

Fig. 5. Elastic registration : (a) initial position (b) affine registration (c) final result

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