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Anatomy Based Multi-modal Medical Image Registration for Computer Integrated Surgery

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Abstract

In Compuer Assisted Surgery (C.I.S), the registration between pre-operative images, intra-operative images, anatomical models and guiding systems such as robots is a crucial step. This paper presents the methodology and the algorithms that we have developed to address the problem of rigid-body registration in this context. Our technique has been validated for many clinical cases where we had to register 3D anatomical surfaces with various sensory data. These sensory data can have 3D representation (3D images, range images, digitized 3D points, 2.5D ultrasound data) or they can be 2D projections (X-ray images, video images).
This paper presents an overview of the results we have obtained

1 Introduction

In Computer Integrated Surgery (C.I.S.) [Taylor et al.94], the registration of all the information available for a given patient is an essential step. For several systems, a crucial step is to estimate an accurate relation between pre-operative images and intra-operative systems. Some authors have proposed to use heavy imaging devices such as CT or MRI directly into the surgical theater (see for instance [Kwoh et al.88]). This approach removes the need for any registration. However, these devices are not easily available in standard surgical theaters, and imaging systems of radiological departements have already difficulties to meet current demand. Another approach is to move the patient until some reference position relative to imaging systems or operating reference systems is reached. For instance, in external radiotherapy, registration of the patient during all irradiation sessions is often reached through the use of crosses or lines drawn on the patient skin and aligned with laser planes that give the irradiation coordinate system. These methods are quite robust but they obviously lack accuracy.

A more convenient approach is to use intra-operative sensors that can be systems already available in surgical theaters (X-ray radioscopy, ultrasound, microscopic or endoscopic imaging systems...) or low-cost vision sensors and then, to use software registration techniques presented in this paper to make pre-operative images virtually available during surgery.

Moreover, in many applications, using only one type of information during surgery is not sufficient. Registration procedures are then required to allow the surgeon or the physician to take the specificity of each information into account. This need of registration between multi-modality information has been already described by many authors as something very useful at the diagnosis level. For instance, PET or SPECT images provide functional information which is necessary to correlate with anatomical images such as CT or MRI [Pelizzari et al.89]. The registration of several MRI taken at different times for a same patient enables to follow the evolution of a tumour. Another instance is the registration of vertebra models derived from CT with dynamic X-rays in order to observe accurately the motion of spine without any approximation [Brunie et al.92].

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Basically, several kinds of data may have to be registered :

- **Pre-operative data**.
  - **Medical Images**. They are usually 2-D or 3-D images : X-rays, ultrasound images, CT, MRI, TEP, SPECT, ... They often constitute the basis of the surgical planning.
  - **Models**. They are usually 3D Atlases, or surface models, and they have a statistical relevance.
  - **Pre-operative positioning information**. They are directly linked to medical images and their unique purpose is to provide information for subsequent registration between medical images and intra-operative systems. This is necessary only when such positioning information is not available on medical images. A typical instance is functional imaging (e.g., SPECT, magnetic imaging with SQUID, ...).
- **Intra-operative data**.
  - **Medical Images**. Intra-operative medical images give information useful to C.I.S. for three reasons: first, they help the surgeon to complete the surgical planning (for instance, intra-operative angiograms help to define a safe path) , second, they provide a real-time intra-operative control of the surgery (for instance, some vascular or other incidents that may occur during surgery are sometimes detectable on intra-operative images), and third, they give positioning information that can be used for registration purposes.
  - **Intra-operative positioning information**. Various sensors give 3D information about the position of organs, in order to perform an accurate registration : optical, ultrasound, mechanical, or electromagnetic 3D localizers, range imaging systems, ...
  - **Intra-operative guiding systems**. Guiding systems that can be passive 3D localizers or active robots have to be registered with the images on which the surgical planning has been defined.
- **Post-operative data.** Data similar to pre-operative data have to be registered to measure the efficiency of an intervention and to update the models.

Obviously, not all applications need to register all types of information previously mentionned. A typical application will have to register pre-operative CT images with a 3D passive or active manipulator during surgery.

In this paper, we are concerned with registration of $3D$ spaces, this registration is based on 3 steps:

1. *definition of a relation between coordinate systems*:

   First, a reference system $\mathrm{Ref_A}$ and $\mathrm{Ref_B}$ is associated with each modality A and B. That implies the estimation of accurate intrinsic calibration functions that transform raw images or sensor data into coordinates given in $\mathrm{Ref_A}$ and $\mathrm{Ref_B}$. See for instance [Champleboux et al.92] for calibration of X-ray images. Then a transformation $\mathbf{T}$ between coordinates of $\mathrm{Ref_A}$ and $\mathrm{Ref_B}$ is defined. For all of registration problems treated in this paper, deformations are considered to be negligible with respect to the required accuracy, therefore a rigid-body transformation $\mathbf{T}$ is used. Rigid-body transformations depend on 6 parameters, they can be represented by a 3-parameters translation vector $\mathbf{T}$ and a 3x3 rotation matrix $\mathbf{R}$ that depends on three parameters. Several possibilities exist to represent rotation matrices. The most popular representation uses Euler angles corresponding to 3 sucessive rotation angles ϕ,θ,ψ around x, y and z axes. See [Szeliski et al.94] for the problem of elastic registration.

2. *segmentation of reference features and definition of a disparity (or similarity) function between extracted features*:

   The second step is to segment reference features in both modalities A and B, and to define a disparity function that depends on the parameters $\mathbf{p}$ of the searched transformation $\mathbf{T}$ and which is minimal when the features are assumed to be matched. Assuming that a gaussian noise is predominant, least squares criterion is often used. For CT / X-ray registration, we will minimize the sum of squares of distances between 3D surface model and 3D projcetion lines issued from contour pixels in X-ray images and obtained by calibration.

3. *optimization of the disparity (or similarity) function*:

To minimize a least squares criterion, direct methods are not always available. Therefore, iterative nonlinear methods are often required: we will use the Levenberg-Marquardt algorithm which has proven to be very powerful for our applications

2 Registration technique

In this section, we briefly present a registration technique that enables us to register a 3D surface model with sensory data. It calculates the rigid-body transformation between two coordinate systems: Ref_{3D} which is associated with the 3D surface model and $\text{Ref}_{\text{sensor}}$ which is associated with sensory data. In general, the 3D model is the result of a segmentation procedure applied to MRI or CT images. Sensory data may be represented by a collection of 3D points obtained through segmentation of a second series of 3D images, through manual digitization of surface points, or through 2.5D ultrasound image segmentation. For all these cases, we apply our 3D-3D registration algorithm. Sensory data may also be 3D projection lines issued from segmented X-ray images, these are the 3D lines corresponding to the external contours of the projected surface. In this case, we apply our 3D-2D registration algorithm.

For both 3D-3D registration algorithm and 3D-2D registration algorithm, it is necessary to precompute and store a 3D distance map associated with the 3D surface model. This distance map is a function that gives the minimum signed 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. The distance map is represented by an octree-spline which is a 3D adaptive and continuous distance map whose resolution increases near the surface, see [Lavallee et al.91] for more details.

The principles of these registration algorithms are now briefly presented:

2.1 3D-3D registration algorithm

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

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

where $\tilde{d}(\mathbf{T}(\mathbf{p})\,\mathbf{q}_i, S)$ is the minimum signed distance between the surface S and the point $\mathbf{q}_i$ transformed by $\mathbf{T}(\mathbf{p})$ in the 3D reference system. The minimization of the error function is performed using the Levenberg-Marquardt algorithm [Press et al.92].The end of the iterative minimization process i s reached either when $E(\mathbf{p})$ is below a fixed threshold, when the gradient of $E(\mathbf{p})$ is below a fixed threshold or when a maximum number of iterations is reached.

2.2 3D-2D registration algorithm

To perform 3D-2D registration, we calculate the projection lines L_i associated with pixels P_i that lie on the external contour of the projection. Projection lines are calculated by a calibration procedure in the sensor reference system $\text{Ref}_{\text{sensor}}$. We then look for the transformation $\mathbf{T}$ between $\text{Ref}_{\text{sensor}}$ and Ref_{3D} that minimizes the energy or error function given by:

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

Figure 1: Convergence of 3-D / 3-D algorithm : In one second, the scalp surface segmented on MRI images converges towards the scalp surface segmented on CT images.

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 transformed by $\mathbf{T}(\mathbf{p})$ of the projection line L_i. σ_i^2 is the variance of the noise of the measurement $\tilde{d}_l(l_i(\mathbf{p}), S)$. $E(\mathbf{p})$ is the weighted sum of squares of the signed distances between the projection lines $l_i(\mathbf{p})$ and the surface S.

A nonlinear least squares iterative minimization of the energy $E(\mathbf{p})$ is also performed using the Levenberg-Marquardt alogorithm [Press et al.92].

3 Results of registration algorithm in clinical cases

In this section we present results of registration obtained in many cases with different types of data.

3.1 *MRI-CT registration using 3D scalp surface*

On Fig.1, 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. 2.

3.2 *SPECT/MRI registration*

For SPECT/MRI registration of the head, no reference structure is available in both modalities for most of cases. Thus we use the idea of adding an external sensor (a range imaging system) to the SPECT device, and to calibrate this sensor with the SPECT images. After calibration, we know the transformation $\mathbf{T}_1$ between the sensor and the SPECT images. By this way, we can use a part of the skin surface as a reference anatomical structure : MRI provides easily the whole skin surface, and the range imaging sensor provides 3D data points that lie on the face (from the middle of the nose to the upper part of the forehead). Fig.3 shows the registration between the range image (a set of surface points) and the surface segmented on MRI images. At the end of the convergence, we obtain the transformation $\mathbf{T}_2$ between the sensor and MRI images. By combining $\mathbf{T}_1$ and $\mathbf{T}_2$ we can calculate the transformation between SPECT and MRI images This technique has been used on several patients and Fig.4 shows a typical instance of SPECT/MRI registration. Tests have shown that the accuracy of this method is about 2 mm, which is better than the SPECT voxel resolution [Peria et al.93].

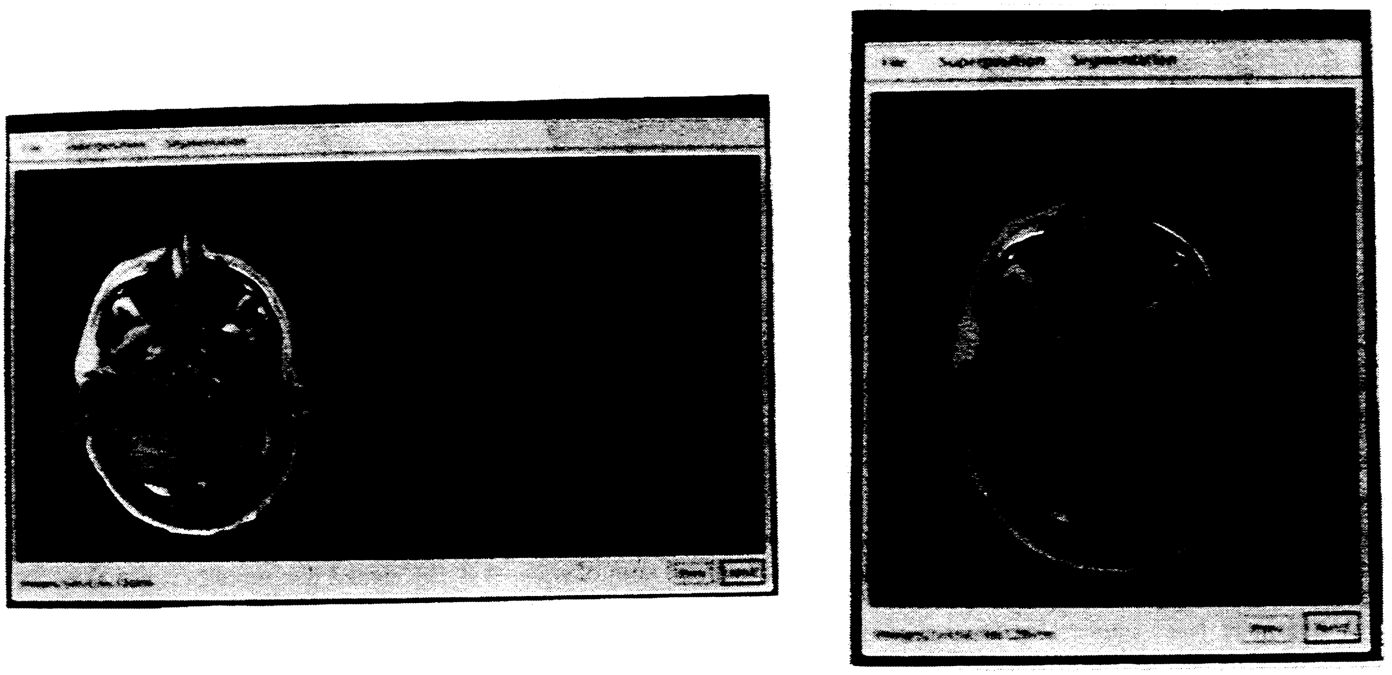

Figure 2: superimposition of MRI and resliced CT images after registration using the scalp surface. The result is visually perfect.

Figure 3: Convergence of 3-D / 3-D algorithm : a set of surface points acquired with a laser range finder converges towards the skin surface of the patient segmented on MRI.

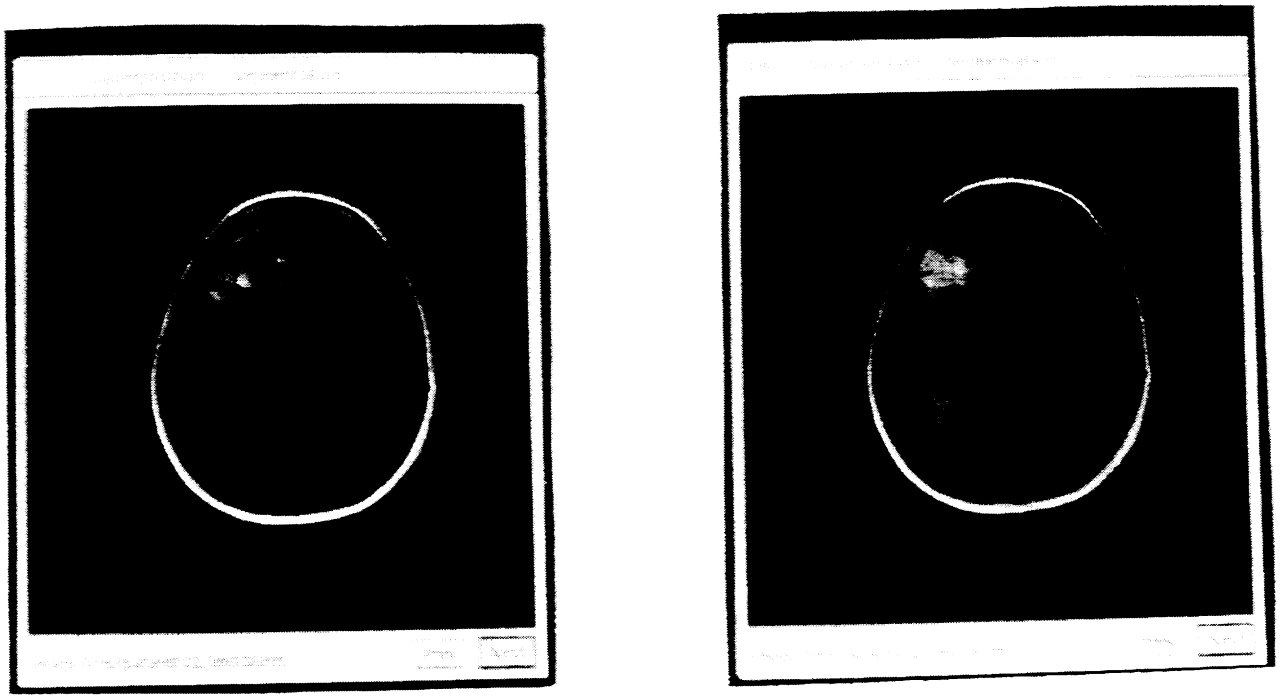

Figure 4: superimposition of MRI and resliced SPECT images after registration on the upper part of the patient's face, using an intermediate range imaging sensor linked to the SPECT device.

3.3 *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 opertation 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 obtained accuracy is better than 1mm. This technique helps the surgeon drill a trajectory which has been defined on pre-operative CT images. Fig 5 show the convergence of registration algorithm between 3D surface points of a vertebra and the 3D surface model of this vertebra. This technique has been applied for open spine surgery [Lavallee et al.94].

3.4 *Registration using an ultrasound probe (2.5D ultrasound pointer)*

Instead of surface points digitization using a simple pointed rod which is put in contact with the vertebra as previously described, we designed a second system that makes use of a standard ultrasound probe to acquire contour points. The idea is to instal a rigid body with infra-red diodes on the ultrasound probe and to calibrate the system so that the location of a pixel of any ultrasound image is known in the 3D space Ref_{intra} associated with an optical localizer. The result is still a set of 3D points in Ref_{intra}, arranged in little pieces of planar curves. This whole system that encompasses the ultrasound image digitization and segmentation is named the *2.5D ultrasound pointer*.

At the end of 3D points acquisition with the 2.5D ultrasound pointer, the 3D/3D registration algorithm is started. A typical convergence is shown on figure 6. With our system configuration, a rapid convergence is always reached and residual errors of the surface registration are usually around 0.8 mm. This technique has been successfully used for accurate patient positionning in external radiotherapy [Troccaz et al.93] and for precutaneous spine surgery [Barbe et al.93]

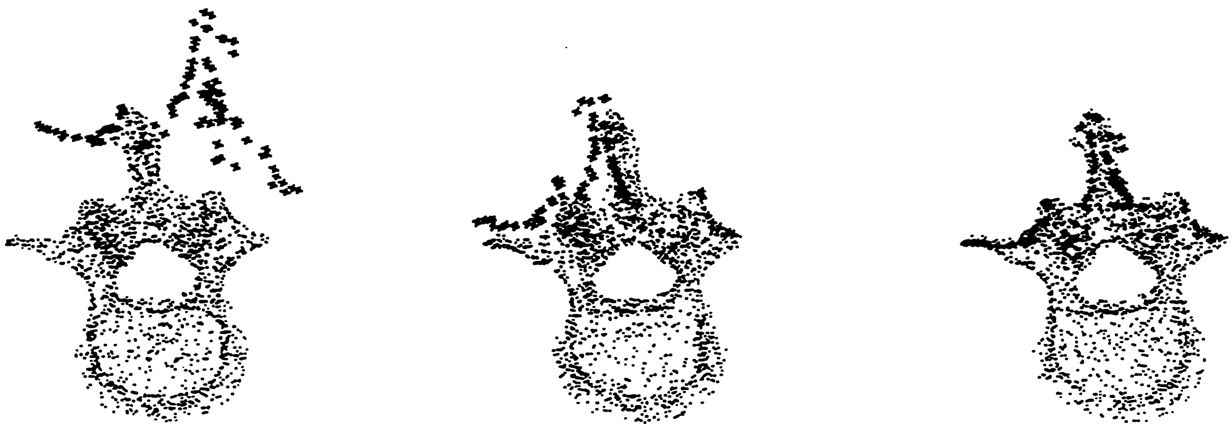

Figure 5: Convergence of 3-D / 3-D algorithm : during spine surgery, a set of surface points acquired manually with an optical 3D localizer converges towards the 3-D model of the vertebra segmented on pre-operative CT images.

Figure 6: Convergence of 3-D / 3-D algorithm : several ultrasound images of the pelvis bone are acquired. The location of the ultrasound probe is determined by an optical localizer. The segmentation of the pelvis bone on all these images gives a set of surface points that can be registered with a CT model previously segmented on CT images.

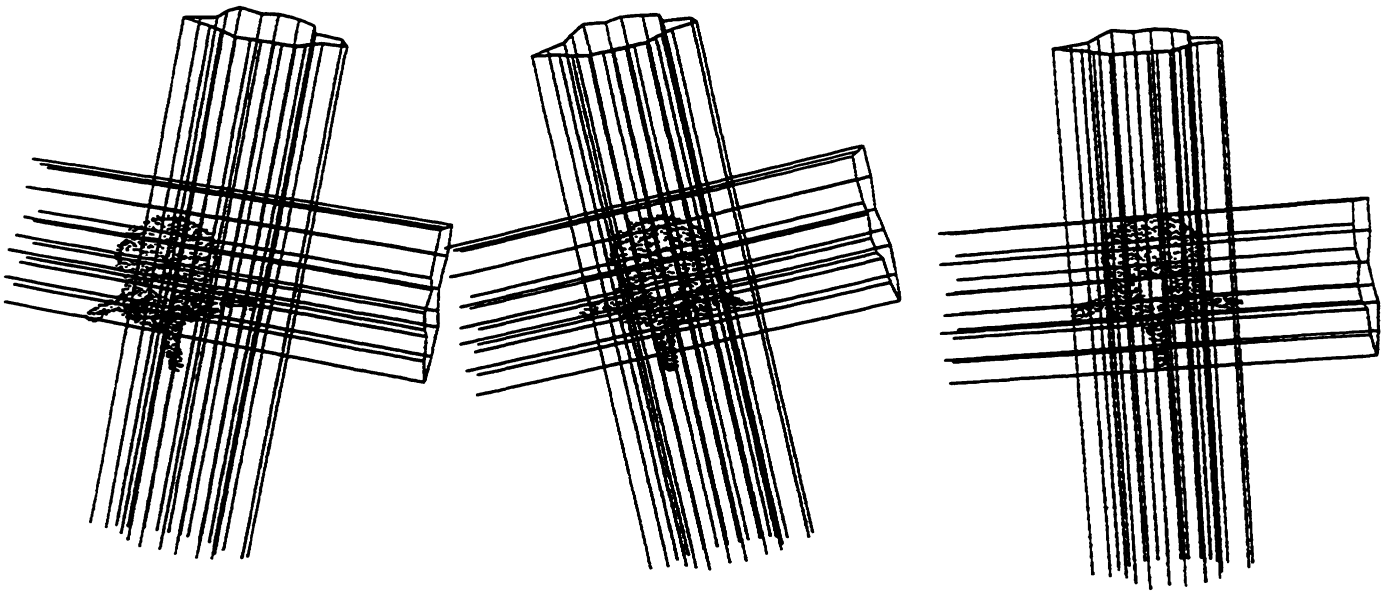

Figure 7: Convergence of 3-D / 2-D algorithm : a set of projection lines issued from a pair of X-rays of a vertebra converges towards the vertebra surface segmented on CT images

3.5 *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. Fig. 7 and Fig. 8 show the convergence of the 3D-2D registration algorithm where the distance between projection lines and 3D surface model of the vertebra or the skull is to be minimized. Independant error measurements were obtained for both cases: less than 1mm for the vertebra, 2mm for the skull. This method has been used for precutaneous spine surgery [Sautot et al.92].

4 Discussion: A unified approach to 3D-2D registration and 2D images Segmentation

The technique used to perform registration between 3D surface models and their 2D projections requires a segmentation step. This segmentation step is necessary to extract the external contours of the projected 3D surface. Once we have extracted external contours, projection lines issued from these contours are built. A nonlinear least squares minimization algorithm is then performed on the error function in order to estimate the rigid-body transformation T between Ref_{3D} and Ref_{sensor}.

The segmentation step of external contours on projection images strongly influences the accuracy of the registration algorithm. This step becomes even more crucial when projection images are not of good quality. The case of X-ray intensifier projection images of the spine is very illustrative. On these images, the manual extraction of external contours is quite difficult and time consuming because of the noise and the overlapping between two successive vertebrae.

The problems of 3D-2D registration and 2D images segmentation are dual. If we can estimate the attitude of the 3D surface model of the visible object in the image, external contours can be easily extracted by projecting the 3D model on the image. If external contours are extracted on projection images, the 3D-2D registration problem is solved as we have already seen.

We propose then to perform automatic extraction of contours on projection images. As a pre-processing step for segmentation, we propose to use the optimal filter of Canny-Deriche to calculate the gradient of projection images. The use of this filter is very interesting for several reasons. It guarantees a good detection of contours (maximum Signal to Noise Ratio), a good localization of contours and an elimination of multiple responses [Canny86]. One parameter α is to be adjusted in order to control the width of the filter. R.Deriche proposed an interesting method to implement this filter recursively with the same number of operation per output value independently from the filter's width [Deriche90].

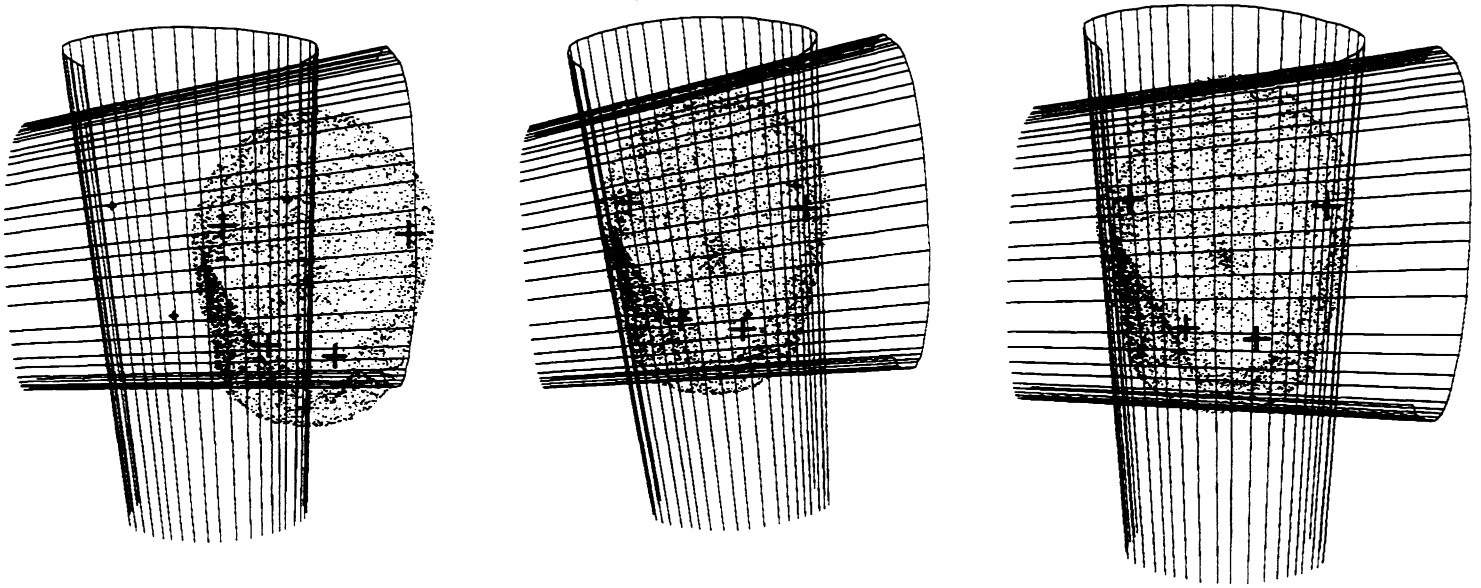

Figure 8: Convergence of 3-D / 2-D algorithm : A set of projection lines issued from a pair of X-rays of the skull converges towards the skull surface segmented on CT images

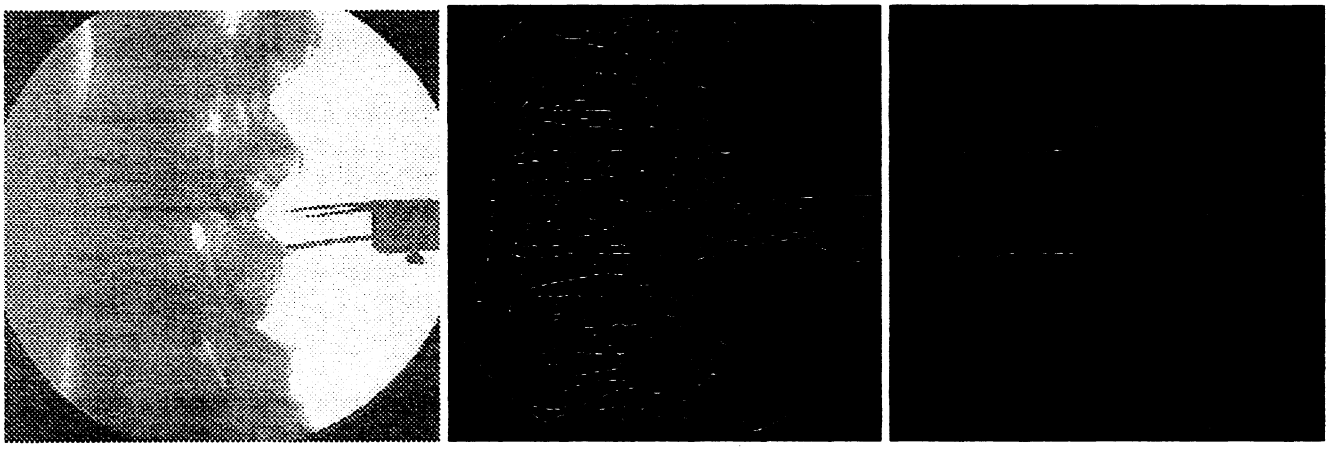

Figure 9: X-ray images of the spine : (a) original imag, (b) pre-segemented images using the Canny-Deriche filter followed by local maxima extraction and hysteresis thresholding, (c) labelled image

Having calculated the gradient image, we perform contour detection by extracting local maxima of gradient in the direction of gradient [Horaud et al.93]. The obtained results are encouraging and show that we can extract the external contours of the vertebral body. Nevertheless, contours of the spineous process of the vertebra are still difficult to extract. A labelling algorithm is applied on local maxima image in order to extract connected contours of the vertebral body which we consider to be likely during the 3D-2D iterative registration process.

Other operators of image analysis may also be used to increase or to decrease the likelihood of extracted contours (laplacian, thresholding, dynamic contours ...etc). We can also use our anatomical knowledge for the same goal. For example, contours of the vertebral body are more likely than contours of other parts of the vertebra, these contextual information may also be taken into account during 3D-2D registration process.

Once the contours of the vertebral body are automatically extracted, we propose to execute the 3D-2D registration procedure as described in section 2.2. This first registration will bring the 3D surface model of the vertebra in a situation which is not far from the searched attitude. In this new attitude, the 3D surface model of the vertebra is projected and the contours of the projection easily extracted. This projected contour helps find the real contours which were not extracted during the first step. For instance, a Distance map associated to the projected contour may contribute to the likelihood of contour pixels on X-ray images. This constitutes our current research.

5 Conclusions

Actually, two classes of registration methods do exist and work in the rigid case :

- *Material-based registration :* using frames, pins, beads, fixed to the patient allows to perform multi-modality registration automatically, accurately and with robustness.

- *Anatomy-based registration :* using reference features segmented on patient data allows to perform multi-modality registration accurately.

Drawbacks of the first approach are obvious for both the patient and the medical staff (invasive methods, difficulty for organization, retrospective registration impossible), which is not the case of the second class of methods. The only drawback of Anatomy-based registration is to use intra-operative sensors. However, these sensors are often available in surgical theaters and they are also useful to update the surgical planning and to control the surgery itself. In future, many issues still have to be addressed. For instance, measuring the registration accuracy for each case is necessary. It may also be required to develop semi-automatic or even automatic segmentation of reference features. So far, fully automated segmentation is restricted to the simplest cases : bones on CT data, skin surfaces on CT or MRI, and obviously surface points extracted with 3D localizers. However, in the future, it is hoped that segmentation and registration will not be considered separately (using iterative feedback of registration on segmentation) so that difficult cases could be solved automatically also. An instance of this approach has been described in this paper, see section 4.

In this paper, we have presented the interest of multi modal medical image registration, the different steps required to perform this registration and the types of data involved in this process. Different results of registration techniques for different data types have also been presented: MRI/CT registration, SPECT/MRI registration, registration using digitization of surface points, registration using an ultrasound probe and registration of 3D surfaces with 2D projections. We have also proposed a new approach to the problems of 3D-2D registration and segmentation of 2D images.

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