Ultrasound to Magnetic Resonance Volume Registration for Brain Sinking Measurement

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Abstract. This paper addresses the registration of ultrasound scans and magnetic resonance (MR) volume datasets of the same patient. During a neurosurgery intervention, pre–operative MR images are often employed as a guide despite the fact that they do not show the actual state of the brain, which sometimes has sunk up to 1 cm. By means of a standard ecographer and a tracker connected to a computer, it is feasible to build on-line an updated picture of the brain. We propose an algorithm which first composes the volume ecography of the brain and registers it to the MR volume. Next, it aligns individual B-scans into the MR volume, thus providing a measure of the suffered deformation.

1 Introduction

The shift of the brain during interventions represents a major source of inaccuracy for any system employing pre-operative images. Because the actual position of the brain during the operation differs from the estimation provided by pre-operative images, the information available to neuronavigators will present systematically misregistrations, and thus surgeons will have to deal manually with possible inconsistencies. Several papers trying to quantify the magnitude and direction of the shift have been reported. A simple approach is to monitor the locations of a number of landmarks in the exposed surface of the brain through the operation. Roberts et al. [3] employ for this purpose an operating microscope on a ceiling-mounted robotic platform with tracking capabilities. The statistical analysis of the recorded positions shows displacement on the order of 1 cm, mostly along the gravity axis.

Maurer et al. [4] employ an intraoperative magnetic resonance (MR) device to acquire a number of scannings during the intervention. This procedure is applied to interventions of different type (biopsies, functional and resections), and then images are analyzed to search for volume changes, and also registered with a non-rigid algorithm based on mutual information.

Other papers aim at the registration of pre-operative to intra-operative images. Roche [5] defines for this purpose a new measure, the correlation ratio, and presents results for several phantoms. It is also interesting Xiao's method [6] for imaging the breast accounting for deformations of the tissue.

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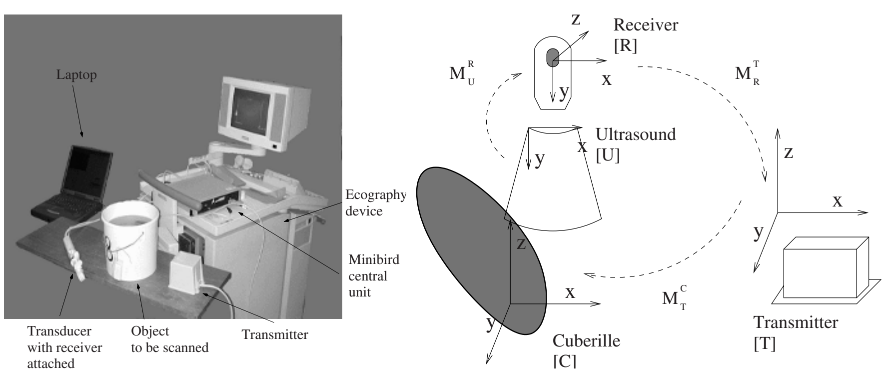
However the proposals in literature are unlikely to be of general use in routine surgery because of their requirements. For instance, those employing intraoperative MR are unavailable to most hospitals due to the cost of a dedicated MR device. Instead of MR , we propose to use ultrasound images for pre-operative image updating. Ultrasound ecography is a popular imaging technique because:

– images are immediately available.
– it is a radiation-free modality.
– the acquisition device is relatively inexpensive and fairly transportable.
– intra-operative ecography devices.

The US acquisition procedure requires the ecography probe to be in physical contact with the surface of the object to be imaged. While the radiologist manipulates the probe along the surface (free-hand scanning), the image displayed in a monitor changes dynamically and he is able to reconstruct mentally the structure underneath the skin. Hard copies of interesting images (individual video frames are called B-scans, $\mathcal{B}$ from here on) are available for a further analysis and measurements.

The free-hand paradigm proposes to track the position of the transducer during the examination, so each $\mathcal{B}$ has a known position and orientation. With this information, the image contents have known spatial location with respect to some external reference system and can be combined to produce a single volume image.



a b

Fig. 1. (a) Picture of the system to acquire and register the US volumes; the laptop (left) would read both the video output of ecography device (top right) and the position from the Minibird tracker (blue box). The transducer was attached with the receiver, while the platform supporting the experiment was metal-free to prevent magnetic interferences. (b) Coordinates systems involved in the free-hand ultrasounding and corresponding transformation matrices : M_U^R from image to receiver, M_R^T receiver to transmitter and M_T^C transmitter to cuberille

Accordingly, we have built a free–hand system, which is able to track the position of the transducer, grab the image acquired at that particular moment and then combine all the information. It consists of the following elements (figure 1a):

- an ultrasound ecographer with video output: Siemens SONOLINE Versa Pro, with three interchangeable probes: 10, 3.5 and 6.5 Mhz.
- a 3-D tracker to measure the position of the ultrasound transducer as accurately as possible: Minibird 800, Ascension Technology, Vermont.
- a device to grab the video frames: Videoport Framegrabber, Transtech systems, Hants, U.K.
- a computer, with two inputs: the ultrasound signal and the tracker position. It is able to store in real time all the incoming data. The computer was a Pentium II working at 366 Mhz and running Microsoft Windows 98.

The data pairs (image, position) can be used to compound a volume image. This volume US image could already be of interest in surgery, since it permits a navigation easier than in the conventional way. But we want to go further: to compare its contents to those of an MR volume, with the final goal of measuring the distances between corresponding features and, eventually, to deform one image according to the other. In this paper we will address only the first part of this goal.

We performed our experiments with an in-vitro adult human brain. This had the advantage to permit the full scan of the surface of the brain, which usually is not feasible during an intervention. For this latter case, only the area immediately below the craniotomy is suitable for scanning. Another advantage was not to depend on the constrains of time of an on-going intervention.

Before proceed on the scanning, the first step was to calibrate the ecography system. Calibration amounts to find out the transformation matrix relating the image coordinate system to that of the receiver and, from there, to the transmitter and the cuberille, an imaginary volume in space where the scanned specimen is contained. For the sake of conciseness, we are not going to develop here this issue. Refer to [7] for an overview of methods and a complete description of the one selected.

Next, we compounded the whole US volume and register it to the MR image (section 2) with an algorithm we already devised and applied to CT –MR volume registration [2]. This first registration step globally aligns the scanned US volume to the usually larger MR one through a rigid transformation. However, it still suffers from the tracker errors, which affect the spatial compounding of the US volume.

But the main cause of misalignment is due to the brain sinking, which is of local nature, and that is precisely what we are interested in. In order to quantify this misalignment, we have proceeded to a second registration step: we have registered individual ecography frames to the MR volume taking as initial position of each B-scan within the MR volume those coordinates given by the global registration transform. As a result we have obtained a preliminary map of deformations similar to those obtained in a real case (section 3), in a form of translation vector to apply to each frame in order to correct the global rigid registration transform.

2 Volume Compounding

After the transducer has been calibrated, the spatial information accompanying each image is used to compound the sequence of video images into a single volume image. To achieve a proper setting of the data, the matrix M_T^C must be chosen carefully to include the area to be imaged. Also, the algorithm must take into account non-scanned voxels and multiply-scanned voxels. For the later case, we have taken the mean value of the pixels with the same final location. Figure 2 shows three orthogonal views of the US volume. Despite the gaps, the features appear fairly constant. We compounded three different volume images of the same in-vitro brain, one for each transducer employed, but we are going to show only images and results for the 10 Mhz transducer, which exhibits the larger depth and field of view.

After building the volume image, the next step was to bring it into alignment with other images. For this purpose, we had taken an MR volume image of the in-vitro brain. The registration did not seem an easy task, as the visual inspection revealed that landmarks were not easy to find in the US volume.

Fortunately, we already had previous experience in similar medical image registration problem [2], and could apply the same algorithm we had employed for CT –MR images. In short, the algorithm has the following characteristics:

- **Feature Space**, this is, the information in the images actually used to compare them. In this case, we segment the contours of the brain, by means of a creaseness-based operator. In effect, sulci (cortical folds) can be seen as valleys in the surface of the brain, and thus can be automatically detected. For a full description, refer to [2]. Achieving a proper segmentation of the sulci is itself a recurrent subject in the literature.
- **Alignment Function.** We take the correlation of the creaseness of the two volumes as the measure of alignment, and consider only rigid transformations.
- **Scheme of Iterative Process.** In order to deal with local maxima, we build a hierarchical structure and iterate the transformations at each level.

We run the algorithm for three compounded US volumes, and successful results did not require any modification of the original algorithm. One can check in figure 2 that the original volumes are visually aligned. Despite the gaps in the image, the shape of the two images is very similar. We have chosen views at the extreme location in the brain to show the most unfavorable case, as misalignments would appear here more clearly. Note that sulci appear much less clearly in the US image than in the MR image. The reason is that small sulci concavities appear as white areas instead of depicting black, empty areas, because the signal is partly reflected back at these points.

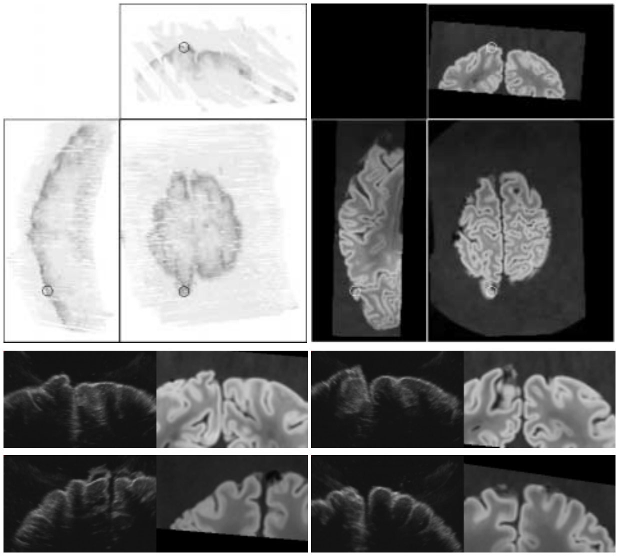


Fig. 2. Top: two corresponding views of US (left) and MR (right) after registering the two volumes. Bottom: B-scan with cutout from registered MR

There is another interesting visualization possibility, which makes use of the whole system of transformations: with the transformation provided by the registration and the matrix M_U^C, it is possible to locate each B-frame into the MR volume, and thus to present its corresponding MR slice. We show corresponding pairs in figure 2. Note that in this slices the alignment seems to be quite good, considering the multiple sources of error and the small size of the image depicted.

3 2D US – 3D US Registration

The registration process performed in the previous section permitted us to relate the coordinates of each video 2–D frame to the MR volume. In a real neurosurgery intervention, there would be some differences between the newly acquired US and the pre–operative MR volume because the tissues would have sunken in some degree. An algorithm could register both images, given the initial estimation of the position provided by volume registration. The resulting transformation would bring locally into alignment the features from both images and would provide an estimation of the deformation needed at that point in order to update the MR volume to the actual features of the brain.

Unfortunately the in-vitro brain could not be employed for this purpose because the tissues were very rigid, and could not be deformed without damage. Yet it is interesting to run a 2D–3D registration with the acquired data, to see whether it can cancel the small positioning errors of the tracking device and,

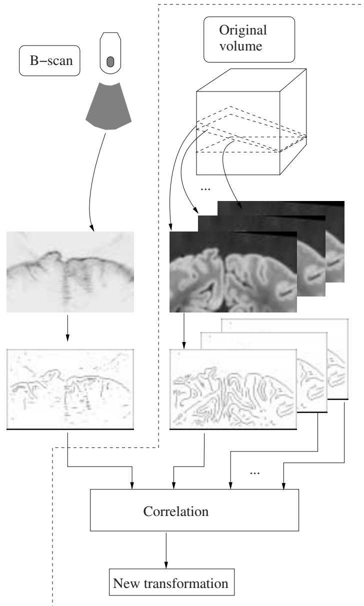


Fig. 3. The iterative part of registration searches new transformations in order to obtain a new cutout more similar to $\mathcal{B}$

more importantly, to correct misalignments due to brain shift. At the same time, the correction vector is a measure of the brain sinking at each frame.

We decided to adapt the creaseness-based algorithm to perform the 2D–3D registration. We modeled the position error as a rigid transformation given by the matrix:

$$M^{ERR} = Trans(T_x, T_y, T_z) \cdot Rot(\phi_x, \phi_y, \phi_z) \tag{1}$$

And we modified the calibration equation (see figure 1b) to include this adjustment:

$$C_{\overline{\mathbf{x}}} = P_{\overline{\mathbf{x}}} \cdot M^{ERR} \cdot M_U^R \cdot M_R^T \cdot M_T^C \cdot M_U^M \tag{2}$$

Recall that M_U^M is the global alignment transform computed in the previous section. We will refer as $\mathcal{C}$ the 2D image in the cuberille, with the coordinates given by the previous equation. M_U^M is the registration matrix computed in the previous section.

The new matrix M^{ERR} measures the error in the position of the slice. We decided to include it in the product before M_U^R because then the units of the transformation would be related to $\mathcal{B}$, i.e., pixels, and not *mm* as it would be the case had we included it after M_T^C .

The next step was to modify our registration algorithm [7] to run with a 2D–3D scheme. The iterative step could be very similar, the only additional step being the computation of $\mathcal{C}$, i.e. the slice to be compared in the volume. The optimization will modify the values of M^{ERR} , which in turn will change the contents of $\mathcal{C}$, until the desired convergence has been achieved.

But the initial step (exhaustive search in the Fourier domain) had to be redesigned, as the dimensionality of the images was different. This initial step could not be suppressed because otherwise the iteration could get trapped in some local maximum. We took the approach to run the 2D–2D registration with the two initial images, the video frame and the corresponding cutout, and then use the result as the first estimation for the 2D–3D algorithm. This approach is schemed in figure

Figure 4 shows the successful convergence for a few frames. Sometimes, the algorithm fails because the compared creases are too dissimilar. Other times, large artifacts appearing in $\mathcal{C}$ mislead the search. Actually, these are the proper results of the creaseness step, only that now the slice is extracted containing the whole surface, instead of a single line as previously. Since the optimization searches the highest correlation value, the search is lead to areas with higher creaseness content. This effect occurs when the initial transformation is poorly estimated because of the lack of reliable landmarks, as it is the case for $\mathcal{B}$ depicting border areas of the brain.

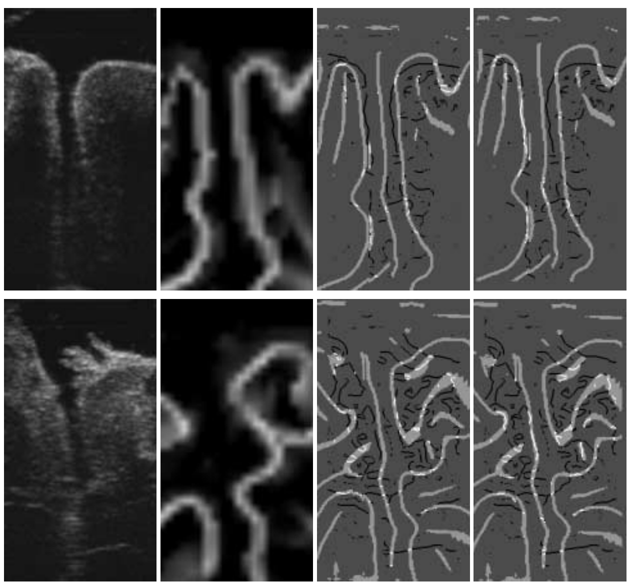


Fig. 4. 2-D to ecography volume registration with the 10 Mhz transducer. First two columns: original $\mathcal{B}$ and $\mathcal{C}$. Third column: superimposed creases, drawn in white when they match, before registration. Forth column: same as third, after registration. Note the difficulty to compare images from different modalities and resolutions, which makes the registration process more difficult

4 Conclusions

We have presented an automatic method for the registration of a compounded US volume to an MR image, already employed for other modalities. The algorithm takes the convolutions of the brain as the landmark to align the volumes. This registration is accurate so as to permit the comparison of the $\mathcal{B}$ image to the corresponding cutout in the MR volume. Furthermore, the 2D–3D registration improves accuracy to one or two pixels in the tested volumes, though more quantitative results are needed to support this conclusion.

An immediate application of this registration is measurement of the sinking of the brain during an intervention in neurosurgery. In effect, the features of each $\mathcal{B}$ scan would be matched against the MR volume, and the obtained transformation would be an estimation of the changes for this particular landmark. Since we have applied the algorithm to an undeformable phantom, we have not been able to fully experiment its trade-offs. In our tests, however, the algorithm could correct well the miss-alignment produced by the errors in the position of the transducer provided by the tracking device. Thus, it would presumably be of relevance in original surgery scenario.

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