Vessel Driven Correction of Brain Shift

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Abstract. In this paper, we present a method for correction of brain shift based on segmentation and registration of blood vessels from pre-operative MR images and intraoperative Doppler ultrasound data. We segment the vascular tree from both MR and US images and use chamfer distance maps and a non-linear registration algorithm to estimate the deformation between the two datasets. The method has been tested in a series of simulation experiments, and in a phantom study. Preliminary results show that we are able to account for large portions of the non-linear deformations and that the technique is capable of estimating shifts when only a very limited region of the brain is covered by the ultrasound volume.

1 Introduction

Modern image guided neurosurgery (IGNS) systems enable the surgeon to navigate within the patient's brain using pre-operative anatomical images (MRI, CT) as a guide. The pre-operative images are related to the patient using a rigid body transformation calculated from a number of anatomical landmarks that can be easily identified on both the patient's head and the pre-operative images. By using a computer-tracked probe during the procedure, the surgeon can localize any point in the patient's brain on the pre-operative images. A significant source of error in these systems is brain tissue movement and deformation, so called brain shift, during the procedure. Tissue movement can be caused by gravity, retraction, resection and administration of medication. The amount of movement and its influence on the accuracy of the neuro-navigation system depend on a number of factors including surgical target location, craniotomy size and patient position during surgery. The magnitude of brain shift is estimated to range from 5mm to 50mm [11,6]. Several strategies have been proposed to quantify and correct for anatomical changes during surgery. Model based techniques have shown to recover up to 80% of the error induced by brain deformation[7,12]. One of the main challenges in this approach is to correctly estimate the mechanical properties of brain tissue which may vary significantly between patients and between tissue types.

The more direct solution to the problem is to acquire new images when significant amount of deformation is suspected. The most popular intraoperative imaging modalities for neurosurgery are intraoperative MRI [1,14], intraoperative CT [13] and intraoperative ultrasound (US) imaging. Even though intraoperative MR imaging provides good quality images in reasonable time, this

C. Barillot, D.R. Haynor, and P. Hellier (Eds.): MICCAI 2004, LNCS 3217, pp. 208–216, 2004.

solution suffers from a number of limitations. Intra-operative MR imaging is a complex, expensive and sometimes time consuming procedure. The intraoperative images are of lessor quality than pre-operative MR images due to scanner design and short acquisition times. Another major shortcoming of this solution is the substantial investment required for the scanner as well as MR-compatible surgical instruments. In many cases, interventional MRI systems also compromises the surgeon's access to the operating field.

Intraoperative ultrasound imaging does not suffer from many of the limitations associated with interventional MRI. A high-end ultrasound scanner costs less than 10% of a typical MRI system and is already in use by many neurosurgeons. In addition, ultrasound systems are portable and compatible with existing surgical equipment. Despite these advantages, the use of ultrasound in neuronavigation has been limited, probably due to poor image quality and limited skills to interpret such images.

Since the mid-1990's a number of groups have developed systems correlating intraoperative US with pre-operative MR. In a neurosurgical context, intraoperative ultrasound imaging can either be used directly as a surgical guide when brain shift occurs [2] or be used as a registration target for the pre-operative images in order to correct for deformations. Roche et al. [9] estimated the rigid body transform required to linearly align pre-operative MR images and intraoperative US images. They correlated the US intensities with both the MR intensity and the MR gradient magnitude using a variant of the correlation ratio and a robust distance measure. They reported registration errors up to 1.65 mm translation and 1.57 deg. rotation.

In order to correct for non-linear deformation Arbel et al. [3] used a tracking system to reconstruct 3D volumes from a series of US images in the same space as the pre-operative MR-image. From the pre-operative MR images, they created pseudo-US images that closely resembled real US images of the same structures acquired during surgery. They then used an intensity based non-linear registration technique to match tracked intraoperative US images with the pseudo-US images to detect and correct brain deformations. Qualitative results from 12 surgical cases showed that the technique was able to account for a large portions of the deformations.

Registration of intraoperative US with pre-operative MR is a challenging registration problem due to very different underlying physical principles and thus different image characteristics. Image intensities, noise characteristics, contrast, volume coverage and dimensionality are only a few main differences between a typical pre-operative MR image and a corresponding intraoperative ultrasound acquisition.

To try to overcome some of these difficulties, we explore a different approach to this particular registration problem. The idea is to use homologous features in the two datasets. Such features might be any segmented structures present in both images such as edges and other easily identifiable landmarks. In this project we investigate the use of blood vessels segmented from pre-operative angiographic images and Doppler US for registration purposes. Blood vessels are relatively easy to identify and segment from both pre-operative angiographic data such as MR angiograms (MRA) or gadolinium enhanced MR images and

from Doppler ultrasound images. The vessels are distributed all over the cortex and inside the brain which means that they will be present in almost any region of interest (ROI). Keeping track of important vessels during surgery also provides the surgeon with important reference points in order to avoid major vessels during the procedure and monitor blood supply to specific areas of the brain.

In this paper we present a method for non-linear registration of pre-operative MR images and intraoperative US data driven by angiographic images. In section 2 we describe the registration technique in detail, and in section 3 and 4 we present a series of simulations and a phantom study in order to test and validate the method. Finally, the results and future work are discussed in the last part of the paper.

2 Methods

The goal of this work is to correct the patient's pre-operative images (anatomical, angiographic, functional,..) for any non-linear brain deformations based on Doppler ultrasound images acquired at different stages during surgery. Before surgery, the patient's angiographic MR images (MRA or gadolinium enhanced MRI) are segmented in order to build a 3D model of the patient's vasculature. Using the 3D model of the vascular tree, we compute a 3D chamfer distance map for use in the registration process. During the surgical procedure, a series of Doppler US images are acquired and reconstructed into a 3D volume using information from the tracking system and the pre-computed probe calibration matrix. The Doppler signal representing the blood vessels is then segmented from the b-mode ultrasound image to obtain a 3D representation of the portion of the vascular tree covered by the US volume. A chamfer distance map is then computed for the US model of the vessels, and used as input to the registration algorithm. Using the two original volumes along with the two chamfer distance maps, we estimate a non-linear deformation field in order to detect any deformation between the pre-operative and intraoperative models of the cerebral vasculature. The resulting deformation field can then be applied to the pre-operative MR images (anatomical and angiographic images) to provide the surgeon with MR images reflecting the surgical reality at any given point during the procedure. These steps will be described in more detail in the following sections.

2.1 Vessel Segmentation

We use a new multi-scale geometric flow for segmenting vasculature in the MR image of the phantom. The method first applies Frangi's vesselness measure [10] to find putative centerlines of tubular structures along with their estimated radii and orientation. This multi-scale measure is then distributed to create a vector field which is orthogonal to vessel boundaries so that the flux maximizing flow algorithm [15] can be applied to recover them. The technique overcomes many limitations of existing approaches in the literature specifically designed for angiographic data due its multi-scale tubular structure model. It has a formal

motivation, is topologically adaptive due to its implementation using level set methods, is computationally efficient and requires minimal user interaction. The technique is detailed in [8].

2.2 Chamfer Similarity Function

The chamfer similarity function has been developed and described by Borgefors [4]. The algorithm has since then been applied in a number of different fields as a technique for finding the best fit of edge points from two different images, by minimizing a generalized distance between them. The algorithm takes binary images representing the edges to register as input. It then computes a chamfer distance map corresponding to the source image. This is an image where every non-edge voxel is given a value approximating the Euclidean distance to the closest edge voxel. The target image is then superimposed onto the distance map and translated and rotated in an iterative manner until the root mean square of the voxels in the distance map corresponding to edge points in the target image is minimum.

Another possible approach is to compute chamfer distance maps for both source and target images and then minimize the difference between the two maps. We found this to be more robust than the classic structure-chamfer matching, it is therefore the technique used in the ANIMAL registration procedure described in the following section.

2.3 Non-linear Registration

In this project we use the ANIMAL registration package [5] to compute the non-linear transformation required to map pre-operative MR to intraoperative US images. ANIMAL estimates a dense three dimensional vector field that gives point to point correspondences between the source and target image. The algorithm works in an hierarchical manner, starting with images blurred with a fwhm of 16mm to estimate the largest deformations, and then refining the transformation by using less blurred data. The algorithm builds up a 3D grid covering the target volume, and performs a search within a user-defined local neighborhood around each node. At each resolution level, the optimal displacement vector is stored for each node in the 3D grid. For the most common registration tasks, ANIMAL uses the cross-correlation similarity function to optimize the fit between the source and target image. However, in this project we incorporate the use of chamfer distance maps and minimization of the simple difference between the two distance maps into the algorithm. Both original images and chamfer distance maps were given as input to the registration algorithm, but the optimization was heavily weighted toward the minimization of the difference between the distance maps with a weight of 1 to 100, for the cross-correlation on the original images and difference between chamfer maps, respectively.

3 Simulations

3.1 Method

A patient's gadolinium enhanced MR image used in the simulations was acquired using a Philips 1.5T Gyroscan (The Netherlands) machine and was segmented manually in order to extract the cerebral vasculature. Following the segmentation, we placed anchor points for a thin plate spline transform throughout the volume. Four points on the cortical surface above the tumor were then manually displaced from 3 to 10 mm in the positive and negative x-direction, which represent a smooth expansion or contraction toward the mid-line of the brain. The thin plate spline transform was then computed between the original point set and the pointset containing the displaced points. The resulting transform was applied to the original image and the segmented vessels, and chamfer distance maps were calculated both for the original and transformed volumes. In order to simulate the situation where the Doppler ultrasound data only covers a small portion of the entire brain, we extracted a region of interest (ROI) of $69 \times 75 \times 70 mm^3$ covering the tumor area from the deformed original image and chamfer map. Finally, the original image, the original chamfer map, the ROI of the deformed image and the ROI of the deformed chamfer map were input to the ANIMAL registration algorithm in order to recover the known transformation.

3.2 Results

The results of the simulations for three different displacements are shown in Table 1. Figure 1 shows the initial difference between the original and the transformed image and the corresponding difference image after non-linear registration extimated in the ROI.

Table 1. RMS3D before and after non-linear registration. The RMS3D error is estimated on a regular grid covering the ROI.

Displacement(mm)	RMS3D before registration(mm)	RMS3D after registration(mm)
5.00	2.37	0.60
-5.00	2.49	0.45
-10.00	5.04	1.03

The results of the simulation experiments presented in this section suggest that the registration technique is able to correctly estimate the deformation between an entire brain volume and a ROI covering only a small portion of the brain. This will almost certainly be the situation in most registration tasks between pre-operative MR and intraoperative US, where the US volume only will cover a limited region around the surgical target, and is therefore an important aspect to verify.

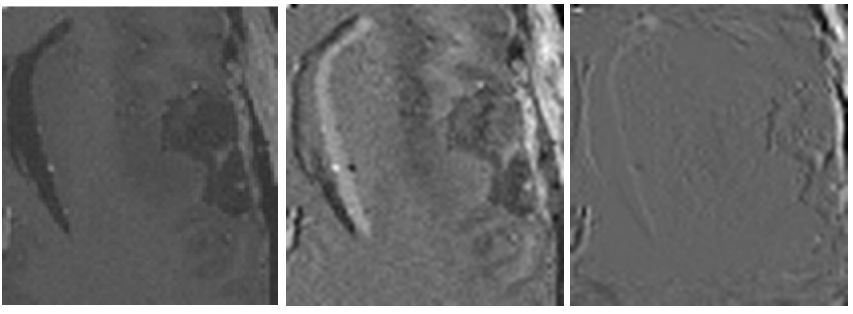

Fig. 1. Left: A transverse slice through the ROI in the original MR image. Middle: Difference image between the original and the transformed image before registration for a displacement of -10 mm. Right: Difference image between the transformed and the deformed original image after registration.

4 Phantom Study

The phantom used in this experiment was made of orange-flavored Jell-o jelly (Kraft Canada Inc., Don Mills, ON). A thin plastic tube was curled and attached to the bottom of a plastic brain mould before filling it with liquid Jell-o. The plastic tube was inserted to simulate the cerebral vasculature. The phantom was then left over night in a fridge to solidify.

4.1 MR Imaging

The phantom was scanned using a Siemens Sonata Vision 1.5T scanner using a standard T1 weighted anatomical scanning sequence with full brain coverage and 1 mm isotropic resolution. The phantom was left in the mould during scanning, and the plastic tube was filled with tap water. Following image acquisition, the vasculature simulated by the plastic tube was segmented from the MR image using the segmentation algorithm described in section 2.1. A surface rendering of the segmented structure is shown in Figure 2. We then computed the chamfer distance map for the segmented MR volume for use in the registration algorithm.

4.2 Ultrasound Imaging and Image Registration

Following MR imaging, the phantom was taken out of the mould and imaged in a container filled with water. Ultrasound images were acquired using an HDI 5000, ATL (Bothwell, WA) ultrasound machine with an ATL P7-4 multi-frequency probe. Tracking was achieved with the use of the Polaris optical tracking system (Northern Digital Inc., Waterloo, ON), a passive reference and an active tracker device (Traxtal Inc., Toronto, ON) attached to the ultrasound probe. We used a physiological pump (Manostat Corp., New York City, NY) to pump water through the plastic tube while we scanned the phantom using color Doppler imaging. Following image acquisition, we masked the images and segmented

the Doppler signal from the b-mode images by simple thresholding. We then computed the extent of the scanned volume and resampled and averaged all the 2D images into the resulting 3D volume. A surface rendering of the segmented structure is shown in Figure 2. Finally, we computed the chamfer distance map for the segmented ultrasound volume.

In order to provide a starting point for the non-linear registration algorithm, we linearly registered the two volumes using a series of manually identified homologous landmarks, as done in surgery. We then applied the non-linear registration technique described in section 2.3.

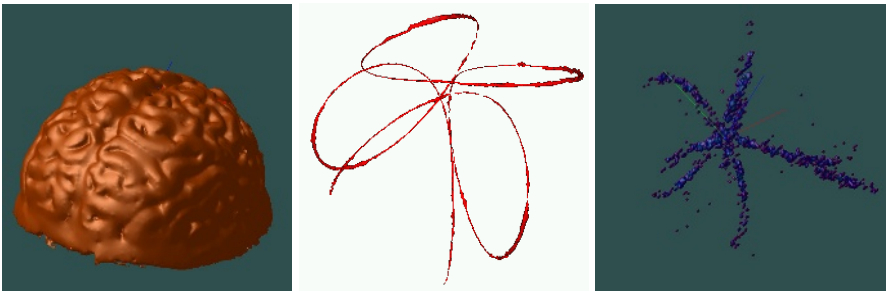

Fig. 2. Surface rendering of the entire phantom to the left,"vessels" segmented from the MR images in the middle and "vessels" from the US volume to the right

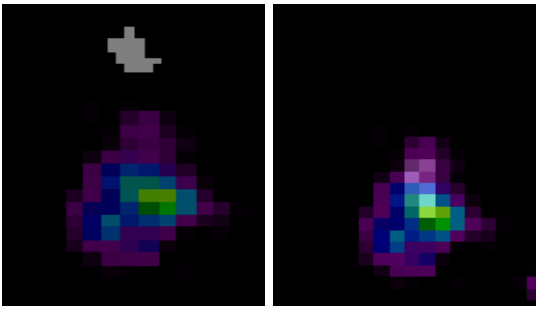

Fig. 3. Cross-section of vessels segmented from MR (white) and Doppler US (color) before (distance=11.36mm) and after (distance=1.41mm) registration.

4.3 Phantom Study Results

Unlike the simulation experiment, the truth is unknown when we register real data. In order to evaluate the performance of the registration in this situation, we measured the distance between vessel centers in MR and US before and after registration. The centers of the vessels were determined manually as the brightest pixel inside the vessel. In the example shown in Figure 3 the distance between

the vessel centers is reduced from 11.36mm before registration to 1.41mm after registration. This is comparable with the results shown in the simulation experiments.

5 Discussion and Conclusions

In this paper, we have presented a new method for correction of brain shift based on blood vessel segmentation and registration. The technique has been tested in a series of simulation experiments, and in a phantom study. It has shown to be able to recover large portions of non-linear deformations even when only a very limited region of the MR image is covered by the US acquisition. While more experiments are required to test the method with real patient data, these initial experiments show that blood vessels have the potential of being very useful features for registration of MR and US images. By using segmented blood vessels, we overcome many of the difficulties associated with registration of US data and will hopefully provide the surgeon with a fast and easy way of getting accurate information about the anatomy and vasculature at any given point during surgery. Future experiments will include more realistic simulations in regard to splitting and reconstuction of the ROI and missing vessels, and a more extensive phantom study. The method will also be tested using real patient data in the near future, and this will give us further indication of areas that will need improvement and optimization.

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