Abstract. Image guided neurosurgery is employed to help surgeons distinguish between healthy and diseased brain tissues, which can have similar visual appearance. It has been our goal to increase the information-content of intraoperative images by tracking volumetric brain deformations intraoperatively, and using this to match preoperative data. A finite element based biomechanical model was used during two neurosurgical procedures to capture non-rigid deformations of critical structures, extracted from a deformable volumetric digital brain atlas. These structures were mapped onto intraoperative Magnetic Resonance (MR) images. Our method meets the real-time constraints of neurosurgery and allows the visualization of multi-modality data, otherwise not available during surgery, together with intraoperative MR data.

1 Introduction

The development of image guided surgery methods over the past decade has permitted major advances in minimally invasive therapy delivery. This has been particularly true for neurosurgical procedures, where the surgeon is faced with the challenge of removing as much tumor as possible without destroying healthy brain tissue. Difficulties are caused by the similar visual appearance of healthy and diseased brain tissue, and by the inability of the surgeon to see critical structures underneath the brain surface as it is being cut. Also, it is now widely recognized that during neurosurgery, due to swelling, hemorrhage, cerebrospinal fluid (CSF) loss and resection itself, the brain undergoes nonrigid deformations [1].

We have rapidly and accurately captured the deformation of the brain during neurosurgery using intraoperative images and a biomechanical registration algorithm developed by Ferrant [2][3][4]. This model has allowed us to align preoperative data to volumetric scans of the brain acquired intraoperatively, and thus improve intraoperative navigation by displaying brain changes in three dimensions (3D) to the surgeon during the procedure.
1.1 Image fusion

Image-guided neurosurgery procedures using intraoperative MR images are carried out in specially-equipped operating rooms, where imaging systems are used to acquire images, as necessitated by the procedure. A number of imaging modalities have been used for image guidance. MR Imaging (MRI) has a significant advantage over other modalities due to its high spatial resolution and superior soft tissue contrast, which has proven to be very useful for image-guided neurosurgery [5]. Intraoperative image acquisition is constrained by factors such as time, magnetic field strength (which inevitably affects image resolution), and equipment availability (which restricts the employment of imaging modalities other than MR). These constraints are less of an issue before surgery, thus presurgical data is often of higher resolution and is able to provide more morphological and functional information than intraoperative data.

Preoperative data acquisition includes modalities that cannot currently be acquired intraoperatively, such as functional MRI (fMRI), nuclear medicine scans, such as Single Photon Emission Computed Tomography (SPECT) and Positron Emission Tomography (PET) scans, and Magnetic Resonance Angiography (MRA). It has been our goal to create a system that allows multi-modality preoperative data to be visualized together with intraoperative MR data. For instance, diffusion tensor MRI provides direct visual information about white matter tracts, while it is difficult if not impossible to manually segment the corticospinal tract from conventional MRI.

1.2 Nonrigid registration for image-guided neurosurgery

During neurosurgical procedures, the spatial coordinates of brain structures and adjacent lesions may change significantly. The leakage of CSF after opening the dura, the administration of anaesthetic and osmotic agents, hemorrhage, hyperventilation, and retraction and resection of tissue are all contributing factors to the intraoperative “brain shift”. This makes information given by preoperatively acquired datasets more difficult to exploit during surgery.

Several image-based and physics-based matching algorithms are being developed to capture these changes in the brain shape, and to create an integrated visualization of preoperative data in the configuration of the deformed brain. We employed a biomechanical model, which ultimately may be expanded to incorporate important material properties of the brain, once these are determined. The approach was to use a finite element discretization, by constructing an unstructured grid representing the geometry of key brain structures in the intraoperative dataset, in order to model important regions while reducing the number of equations to be solved. The rapid execution times required by neurosurgical operations were achieved by using parallel hardware configurations, along with parallel and efficient algorithm implementations [6].

1.3 Tracking of critical brain structures with a deformable volumetric atlas

Previous work by Kaus [7] has shown that it is possible to track anatomical structures, such as the corticospinal tract, even if diffusion tensor data is not available during surgery. This was achieved by aligning a deformable volumetric digital brain atlas onto
brain scans of tumor patients that were acquired intraoperatively, and by estimating spatial correspondence between atlas and patient brain. Affine registration and non-rigid registration based on 3D adaptive template matching techniques allowed accurate matching of the corticospinal tract to the patient brain retrospectively.

Tracking the corticospinal tract is helpful in cases where the tumor is located in its proximity. Such situations are frequent, however it is not unusual that other critical structures are located near the tumor site, and thus need to be tracked during neurosurgery. Examples of such structures are parts of the visual system: the optic radiation and the lateral geniculate body. We therefore show the application of our algorithm to one case where the tumor is located anterior to the pre-central gyrus, very close to the corticospinal tract, and to another case, where the tumor is located in the posterior left temporal lobe, in close anatomical relationship to the optic radiation.

Our method uses a finite element model, which simulates brain elastic properties, to infer the deformation fields captured from the intraoperative image updates and compensate for brain shift during neurosurgery. This algorithm was designed to allow for improved surgical navigation and quantitative monitoring of treatment progress in order to improve the surgical outcome and to reduce the time required in the operating room. To our knowledge, this represents the first time such an approach has been applied prospectively, rather than retrospectively using images acquired during the surgical procedure for post-processing purposes. High-performance computing is a key enabling technology that allows the biomechanical simulation to be executed quickly enough to be practical in clinical use during neurosurgery.

A deformable volumetric brain atlas, based on MR imaging of a single normal male where each voxel was labeled according to its anatomical membership [8], was used to map brain structures onto images acquired during three neurosurgery cases. For the purpose of hierarchical registration, a separate template volume containing only one structure (i.e. the corticospinal tract or the optic radiation) was extracted. This allowed the visualization of complex anatomical information that would otherwise require the use of additional modalities during neurosurgery.

2 Method

2.1 Intraoperative segmentation and rigid registration

Figure 1 shows how the deformable atlas was matched to intraoperatively acquired datasets. First, the patient scan was segmented intraoperatively either through an automated multi-channel tissue classifier [9] or through a binary curvature driven evolution algorithm [10]. The region identified as brain was then interactively corrected to remove any portion of misclassified skin and muscle using the software described by Gering [11]. Such procedure was repeated to obtain a segmentation of the lateral ventricles of the subject. This approach allows the neurosurgeon to inspect the segmentations as they are constructed during the surgery and enhances the surgeon’s confidence in their quality.

Next, the atlas was registered to the patient’s scan by means of a parallel implementation of an affine registration algorithm developed by Warfield [12]. In addition to
translation and rotation, accounted for by rigid registration methods, affine registration algorithms also scale the image, as the head size may be slightly different. This factor is very important for an atlas match, but it can be discarded when matching preoperative patient data. The affine registration method is a very fast algorithm to register preoperative to intraoperative images. However, a previous segmentation of the intracranial cavity is required to achieve high speeds.

Thus, we have successfully experimented with a different approach (not shown in the flowchart), which places the rigid registration step before any intraoperative segmentation is carried out. During surgery, the atlas data was aligned with the intraoperative greyscale data using a mutual information (MI) based rigid registration method developed by Wells [13]. The intraoperative image data then together with the previously created (by computing a saturated distance transform of each tissue class - specifically brain and lateral ventricles) volumetric spatial localization model formed a multichannel 3D dataset. This multichannel dataset was segmented with a spatially varying classification as described in [9].

2.2 Surface matching and biomechanical model of brain deformation

A physics-based biomechanical simulation of brain deformation [3][4][14] was employed to nonrigidly register atlas to intraoperative data. This can be summarized as a four-step process. 1) An unstructured mesh was generated, where an explicit representation of the surface of the brain and lateral ventricles was extracted based on the preoperative segmentation. Also, a volumetric unstructured mesh was created using a multiresolution version of the marching tetrahedra algorithm. 2) The surfaces of the brain and of the ventricles were iteratively deformed using a dual active surface algorithm. 3) The displacements obtained by the surface matching were applied to the volumetric model generated in step 1. The brain was treated as a homogeneous linearly elastic material. 4) Finally, the volumetric deformation fields were applied to the
deformable atlas, from which critical structures were extracted to be displayed to the surgeon. The detailed implementation of all these steps is fully described in [2].

Once the next set of scans were obtained and segmented, new meshes were generated, the next set of surfaces were matched, and a new deformation field was calculated and applied to the previously matched atlas data. As mentioned in the introduction, the structures to be tracked vary from case to case. Thus, this atlas provides a great flexibility because the structures are extracted as the very last step. In this manner, successive scans were matched during the procedure. The entire procedure, including segmentation and deformable registration, was completed in less than 12 minutes.

2.3 Intraoperative visualization

The registered atlas structures were visualized using an integrated system described by Gering [11] that allows the display of intraoperative images along with preoperative data, including surface renderings of previous triangle models and arbitrary interactive resampling of 3D grayscale data. This system also allows for visualization of virtual surgical instruments in the coordinate system of the patient and patient image acquisitions (see figure 4). The image we constructed was presented on the LCD monitor in the operating room, and increased the information available to the surgeon as the operation progressed.

3 Results

Figure 2 shows two registered slices of two grayscale images acquired intraoperatively, in which the brain shift is very evident. The left image was acquired before skin incision. The first intraoperative imaging update, acquired after performing some degree of resection, is presented on the right. Upper slices show a region near the lesion, in this case an infiltrative low-grade glioma located anterior to the motor strip, in proximity to the corticospinal tract. Lower slices show that, even away from the lesion, the brain shift is very pronounced.

Models of brain structures of the second case are shown in Figure 3. Brain (white), ventricles (blue), tumor (green), and optic radiation (red) were created in an advanced stage of resection. The brain shift is very evident. The close spatial relationship between lesion and optic radiation is obvious, thus it was very critical to track this structure.

Figure 4 shows the initial MR dataset of the first case aligned with the corticospinal tract extracted from the deformed atlas, displayed with the virtual surgical needle, interactively tracked within the patient’s coordinate system. This was displayed to the surgeon in the operating room only a few minutes after the MR image was acquired intraoperatively. Figure 4 also depicts volumetric deformation fields between the first and second intraoperative scan volume, shown aligned with a model of the corticospinal tract. The color-coding indicates the magnitude of the deformation at every point on the slice of the deformed volume.

Figure 5 presents two views of surface and volumetric deformation fields between the first and second intraoperative scan volume. The color-coding indicates the magnitude of the deformation at every point on the surface or cuts of the deformed volume, and arrows indicate the magnitude and direction of the deformation.
Fig. 2. Intraoperative MR images. Left: initial image, acquired before skin incision. Right: first intraoperative imaging update, acquired after performing some degree of resection. Upper slices show a region near the lesion. Lower slices show that, even away from the lesion, the brain shift is very pronounced.
Fig. 3. Post-resection models of brain (white), ventricles (blue), tumor (green), and optic radiation (red). The tumor is clearly located next to the optic radiation. After most of the resection, the brain has shifted significantly.
Fig. 4. MR image (as shown in figure 2, on the left) and visualization of volumetric deformation fields between first and second intraoperative volume, both aligned with the corticospinal tract. The color-coding indicates the magnitude of the deformation at every point on the slice of the deformed volume.
Fig. 5. Visualization of surface and volumetric deformation fields of the first intraoperative scan volume onto the second intraoperative scan volume of the first case, aligned with the corticospinal tract. The color-coding indicates the magnitude of the deformation at every point on the surface or cuts of the deformed volume, and arrows indicate the magnitude and direction of the deformation.
4 Discussion and Conclusion

Figure 6 shows models of the brain (white), ventricles (blue), residual tumor (green) and optic radiation (red), along with the intraoperatively acquired MR dataset. These models were created in an advanced stage of resection (during the second case). This figure underlines that both intraoperative image acquisition and a robust nonrigid registration algorithm are essential for accurate multi-modality image fusion during neurosurgery.

In spite of significant anatomical differences between atlas and patient, the deformation was accurately calculated and we were able to register the atlas corticospinal tract and the optic radiation to the patient anatomy. There is a small registration error due to the fact that patient and atlas brain have a different morphology. In these initial experiments, the atlas was used as a surrogate for preoperative data from different imaging modalities (MRA, fMRI, etc.). We are currently conducting more rigorous validation studies using segmented preoperative data to create a patient-specific atlas. We plan to incorporate diffusion tensor imaging to better visualize white matter tracts.

Currently, image segmentation algorithms, used to identify key surfaces for the biomechanical simulation of deformation, rely upon image signal intensities. A strong model of the prior probability of the spatial distribution of brain and ventricles would
help to improve the robustness and speed of the image segmentation. Such a model could be derived by aligning large numbers of subjects’ scans and then measuring the empirical distribution of tissue classes.

We are also aiming to expand the biomechanical model to incorporate an anistropic inhomogeneous white matter material model, and include a nonlinear, potentially hyper-visco-elastic framework. In addition, we plan to perform intraoperative measurements of brain material properties, and then to include these physiological parameters in our modeling system. We expect that the fusion of patient-specific multi-modality data and the use of an improved biomechanical model will provide more accurate intraoperative matches. This method has the potential to increase the information-content of intraoperative images and to enable an accurate description of surgical changes.

References


