Real-Time Biomechanical Simulation of Volumetric Brain Deformation for Image Guided Neurosurgery

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Abstract

We aimed to study the performance of a parallel implementation of an intraoperative nonrigid registration algorithm that accurately simulates the biomechanical properties of the brain and its deformations during surgery. The 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. We have applied the algorithm to two neurosurgery cases with promising results.

High performance computing is a key enabling technology that allows the biomechanical simulation to be executed quickly enough for the algorithm to be practical. Our parallel implementation was evaluated on a symmetric multi-processor and two clusters and exhibited similar performance characteristics on each. The implementation was sufficiently fast to be used in the operating room during a neurosurgery procedure. It allowed a three-dimensional volumetric deformation to be simulated in less than ten seconds.

1 Introduction

The key challenge for the neurosurgeon during brain surgery is to remove as much as possible of a tumor without destroying healthy brain tissue. This can be difficult because the visual appearance of healthy and diseased brain tissue can be very similar. It is also complicated by the inability of the surgeon to see critical structures underneath the brain surface as it is being cut. It was our goal to be able to rapidly and faithfully capture the deformation of the brain during neurosurgery, so as to improve intraoperative navigation by allow preoperative data to be aligned to volumetric scans of the brain acquired intraoperatively.

Image guided surgery techniques are used in operating rooms equipped with special purpose imaging equipment. The development of image guided surgical methods over the past decade has provided a major advance in minimally invasive therapy delivery.

Image guided therapy has largely been a visualization driven task. Quantitative assessment of intraoperative imaging data has not been possible in the past, and instead qualitative judgements by experts in the clinical domains have been relied upon. In order to provide the surgeon or interventional radiologist with as rich a visualization environment as possible from which to derive such judgements, previous work has primarily been concerned with image acquisition, visualization and registration of...
intraoperative and preoperative data. Biomechanically accurate registration of brain scans acquired during surgery, as proposed here, has the potential to be a significant aid to the automatic interpretation of intraoperative images and to enable prediction of surgical changes.

Early work (reviewed by Jolesz [1]) has established the importance and value of image guidance through the better localization of lesions, the better determination of tumor margins, and the optimization of the surgical approach. Previous algorithm design has been a steady progression of improving image acquisition and intraoperative image processing. This has included increasingly sophisticated multimodality image fusion and registration. Clinical experience with image guided therapy in deep brain structures and with large resections has revealed the limitations of existing rigid registration and visualization approaches [1].

The changes in brain shape during neurosurgery are now widely recognized as nonrigid deformations. Suitable approaches to capture these deformations and to allow integrated visualizations of preoperative data matched to the brain as it changes shape during the course of surgery are in active development. Previous work in capturing brain deformations for neurosurgery can be categorized by those that use some form of biomechanical model (recent examples include [2–4]) and those that apply a phenomenological approach relying upon image related criteria (recent examples include [5, 6].)

A fast surgery simulation method was described in [7] which achieved speed by converting a volumetric finite element model into a model with only surface nodes. This work had the goal of achieving interactive graphics speeds at the cost of accuracy of the simulation. Such a model is applicable for computer graphics oriented visualization tasks but during neurosurgical interventions on patients we aim for as high accuracy and robustness as possible and use parallel hardware to achieve clinically compatible execution times.

A sophisticated biomechanical model for two-dimensional brain deformation simulation using a finite element discretization was proposed in [2]. However this work used the pixels of the two-dimensional image as the elements of the finite element mesh, and relied upon manually determined correspondences. Unfortunately, two-dimensional results are not useful in clinical neurosurgical practice and such a discretization approach is extremely computationally expensive (even considering a parallel implementation) if expanded to three spatial dimensions because of the large number of voxels in a typical intraoperative MRI (256x256x60 ≈ 4e06 voxels) leading to a large number of equations to solve. Instead, the use of a finite element model with an unstructured grid can allow a representation that faithfully models key characteristics in important regions while reducing the number of equations to solve by using mesh elements that cover several image pixels in other regions.

Most meshing software packages used in the medical domain do not allow meshing of multiple objects [8, 9], and often work best with regular and convex objects, which is usually not the case for anatomical structures. Therefore, we have implemented a tetrahedral mesh generator specifically suited for labeled 3D medical images. The mesh generator can be seen as the volumetric counterpart of a marching tetrahedra surface generation algorithm. A detailed description of the algorithm can be found in [10]. The resulting mesh structure is built such that for images containing multiple objects, a fully connected and consistent tetrahedral mesh is obtained for every cell. A segmentation of the image indicates the type of anatomical structure the cell belongs to. Therefore, different biomechanical properties and parameters can easily be assigned to the different cells or objects composing the mesh. Boundary surfaces of objects represented in the mesh can be extracted from the mesh as triangulated surfaces, which is convenient for running an active surface algorithm, as described below.

A number of imaging modalities have been used for image guidance. These include, amongst others, digital subtraction angiography (DSA), computed tomography (CT), ultrasound (US), and magnetic resonance imaging (MRI). Intraoperative MR imaging can acquire high contrast images of soft tissue anatomy which has proven to be very useful for image-guided therapy [11]. Multi-modality
registration allows preoperative data that cannot be acquired intraoperatively, such as functional MRI (fMRI) or nuclear medicine scans, such as Positron Emission Tomography (PET) or Single Photon Emission Computed Tomography (SPECT) scans, or magnetic resonance angiography (MRA) to be visualized together with intraoperative data.

A system for intraoperative visualization has recently been developed [12]. This system allows surface rendering of previously prepared triangle models and arbitrary interactive resampling of 3D grayscale data. The system also allows for visualization of virtual surgical instruments in the coordinate system of the patient and patient image acquisitions. The system supports qualitative analysis based on expert inspection of the image data and the surgeons expectation of what should be present (normal anatomy, pathology, current progress of the surgery etc.) The ability to automatically capture the deformation of the brain during neurosurgery would allow the augmentation of such a system to enable the visualizations prepared preoperatively to be updated to follow the changes that occur during surgery. For example, this might allow previously acquired functional MRI (which cannot be acquired intraoperatively) to be transformed to place the functional information in alignment with intraoperatively acquired morphologic MRI, preserving the ability to interpret areas of the morphologic MRI based upon the functional information.

We aimed to demonstrate that a volumetric three-dimensional biomechanical simulation of brain deformation is possible even with the time constraints of neurosurgery and that such simulations significantly add to the value of intraoperative imaging and hence improve surgical outcomes.

2 Method

In order to successfully capture brain deformation from intraoperative images we have developed a set of image processing algorithms that take advantage of an existing preoperative MR acquisition and segmentation. We have experimented for several years with a general image segmentation approach that uses a 3D digital anatomical atlas to provide automatic local context for classification [13–16]. In this application the preoperative data acts as a patient-specific atlas which enables a robust and reliable intraoperative segmentation of the brain surface of the patient using our previously described real-time segmentation algorithm [17]. The brain segmentation then constitutes a reliable target for the biomechanical simulation of the brain deformation. Figure 1 illustrates the processing steps that take place before and during the therapy procedure.

Since preoperative data is acquired before surgery, the time available for segmentation is longer.
This means we can use segmentation approaches that are as robust and accurate as possible but are time consuming and hence impractical to use in the operating room. In our laboratory, preoperative data is segmented with a variety of manual [12], semi-automated [18] or automated [15, 16] approaches. We attempt to select the most robust and accurate approach available for a given clinical application. Each segmented tissue class is then converted into an explicit 3D volumetric spatially varying model of the location of that tissue class, by computing a saturated distance transform [19] of the tissue class. This model is used to provide robust automatic local context for the classification of intraoperative data in the following way.

During surgery, intraoperative data is acquired and the preoperative data (including any MRI, fMRI, PET, SPECT, MRA that is appropriate, the tissue class segmentation and the spatial localization model derived from it) is aligned with the intraoperative data using an MI based rigid registration method [12, 20]. The intraoperative image data then together with the spatial localization model forms a multichannel 3D data set. Each voxel of the combined data sets is then represented by a vector having components from the intraoperative MR scan, the spatially varying tissue location model and if relevant to the particular surgery, any of the other preoperative image data sets. For the first intraoperative scan to be segmented a statistical model for the probability distribution of tissue classes in the intensity and anatomical localization feature space is built. The statistical model is encoded implicitly by selecting groups of prototypical voxels which represent the tissue classes to be segmented intraoperatively (less than five minutes of user interaction). The spatial location of the prototype voxels is recorded and is used to update the statistical model automatically when further intraoperative images are acquired and registered. This multichannel data set is then segmented with $k$-NN classification [14, 21], a standard classification method which computes the type of tissue present at each voxel by comparing the signal of the voxel to classify with the signal of previously selected prototype voxels of known tissue type.

The segmentation of the intraoperative data helps to establish explicitly the regions of tissues that correspond in the preoperative and intraoperative data. In the past we have described an image-based nonrigid registration algorithm [22, 23] which has been successfully applied to capture shape variation in schizophrenia [24]. However, our previous approach does not constitute an accurate biomechanical simulation of the deformation, and hence it is not possible to effectively model the different material properties of different structures in the head, and it is not possible to use such an approach for quantitative prediction of brain deformation. These limitations are addressed by the biomechanical simulation approach we describe below.

2.1 Method for Biomechanical Simulation of Three-Dimensional Volumetric Brain Deformation

Our intraoperative image acquisition and processing identifies the region of the brain volume. However, its shape changes during surgery. The goal of simulating the intraoperative brain volume deformation is to project data aligned with the brain in a previous configuration onto the brain in its new configuration following surgical changes.

We use a two step process to achieve this. In the first step, an active surface algorithm is used to establish the correspondences between the surfaces of the brain data. In the second step the volumetric brain deformation implied by the surface changes is computed using a biomechanical model of the structure of the brain.

The deformation field obtained for the surfaces is used in conjunction with the biomechanical volumetric model to infer the deformation field inside and outside the surfaces. The key concept is to apply forces to the volumetric model that will produce the same displacement field at the surfaces.
as was obtained with the active surface algorithm. The biomechanical model will then compute the deformation throughout the volume.

2.1.1 Correspondence Detection with an Active Surface

The active surface algorithm iteratively deforms the surface of the first brain volume to match that of the second volume. This is done iteratively by applying forces derived from the volumetric data to an elastic membrane model of the surface. The derived forces are a decreasing function of the data gradients, so as to be minimized at the edges of objects in the volume. To increase robustness and the convergence rate of the process, we have included prior knowledge about the expected gray level and gradients of the objects being matched. This algorithm is fully described in [25].

2.1.2 Biomechanical Simulation of Volumetric Brain Deformation

Assuming a linear elastic continuum with no initial stresses or strains, the potential energy of an elastic body submitted to externally applied forces can be expressed through a finite element model as [26]:

$$ E = \frac{1}{2} \int_{\Omega} \sigma^T \varepsilon \, d\Omega + \int_{\Omega} F \, u \, d\Omega $$

where $F = F(x, y, z)$ is the vector representing the forces applied to the elastic body (forces per unit volume, surface forces or forces concentrated at the nodes of the mesh), $u = u(x, y, z)$ the displacement vector field we wish to compute, and $\Omega$ the body on which one is working described by a mesh of tetrahedral elements. $\varepsilon$ is the strain vector and $\sigma$ the stress vector, linked to the strain vector by the material’s constitutive equations.

In the case of linear elasticity, with no initial stresses or strains, this relation is described as $\sigma = (\sigma_x, \sigma_y, \sigma_z, \tau_{xy}, \tau_{yz}, \tau_{xz})^T = D\varepsilon$, where $D$ is the elasticity matrix characterizing the material’s properties [26].

The continuous displacement field $u$ everywhere within each element of the mesh is defined as a function of the displacement at the element’s nodes $\mathbf{u}_i^e$ weighted by the element’s shape functions (interpolating functions) $N_i^e(\mathbf{x})$,

$$ u(\mathbf{x}) = \sum_{i=1}^{N_{\text{nodes}}} N_i^e(\mathbf{x}) \mathbf{u}_i^e. $$

The elements we use to represent volume data are tetrahedral ($N_{\text{nodes}} = 4$), with linear interpolation of the displacement field. Hence, the shape function of node $i$ of tetrahedral element $e$ is defined as

$$ N_i^e(\mathbf{x}) = \frac{1}{6V^e} \left( a_i^e + b_i^e x + c_i^e y + d_i^e z \right) $$

The computation of the volume of the element $V^e$ and the interpolation coefficients are detailed in [26, pages 91–92].

The volumetric deformation of the brain is found by solving for the displacement field that minimizes the energy described by Equation 1, after fixing the displacements at the surface to match those generated by the active surface model. We solve the system of equations with the Portable, Extensible Toolkit for Scientific Computation (PETSc) package [27, 28] using the Generalized Minimal Residual (GMRES) solver with block Jacobi preconditioning.
Figure 2: Intraoperative magnetic resonance imaging scanner in which image guided therapy takes place. The operating room consists entirely of equipment safe to use around a 0.5T magnetic field. For neurosurgery cases the patient is typically placed lying inside the two toroidal magnets and the surgeon stands in the gap between them.
### 2.2 Hardware for Intraoperative Image Acquisition and Parallel Computation

Figure 2 shows an open-configuration magnetic resonance scanner optimized for imaging during surgical procedures [1, 11]. Operations take place with the patient on the bed inside the toroidal magnets and the surgeon standing in the gap between them.

Measurements of parallel performance were made on three different parallel architectures. The first of the three architectures was a parallel cluster, called “Deep Flow”, consisting of a cluster of Alpha-based workstations running Linux connected by 100Mbps full duplex Fast Ethernet. The specifications of this cluster is described in Table 3. The second architecture was a Sun Microsystems Ultra HPC 6000 symmetric multi-processor machine with 20 250MHz UltraSPARC-II (4MB Ecache) CPUs and 5 GB of RAM. The third architecture was a cluster of two symmetric multi-processor Ultra 80 workstations, each with four 450MHz UltraSPARC-II (4MB Ecache) CPUs and 2GB RAM networked with 100Mbps Fast Ethernet.

### 3 Results

In this section illustrative visualizations of biomechanical simulation of intraoperative brain shift are presented along with an analysis of the performance of our parallel implementation. During surgical procedures in the brain, intraoperative MRI (IMRI) data was acquired and stored. Segmentation and nonrigid registration was applied to this data after therapy delivery in order to allow us to assess the robustness, accuracy and time requirements of the approach. In the future we intend to carry out segmentation, nonrigid registration and visualization using the approach described here during the interventional procedures with the goal of improving image guided therapy outcomes.

#### 3.1 Biomechanical Simulation of Volumetric Brain Deformation

In each neurosurgery case several volumetric MRI scans were carried out during surgery. The first scan was acquired at the beginning of the procedure before any changes in the shape of the brain took place, and then over the course of surgery other scans were acquired as the surgeon checked the progress of tumor resection. The final scan in each sequence exhibits significant nonrigid deformation and loss of tissue due to tumor resection. In order to test our biomechanical simulation approach each subsequent scan was aligned to the first by rigid registration using maximization of mutual information. This method computes a global alignment accounting for positioning differences in the scan.
coordinates but does not attempt to correct for nonrigid deformation. The first scan was manually segmented to act as an individualized anatomical model. The last scan in each sequence was then segmented with our intraoperative segmentation approach. Our algorithm for biomechanical simulation of the brain deformation was then executed to compute the volumetric deformation between the two data scans.

In order to check the quality of the registration, the deformation of the first MRI scan was visually compared with the MRI to which it was matched. In each case the registered brain closely matched the expected location. Figure 4 is a visualization of the accuracy of the recovered volumetric deformation illustrated with two-dimensional slices.

Figure 4(a) shows the skin bright, the brain gray and the lateral ventricles dark, in its initial configuration. This defines the coordinate system in which preoperative data is aligned and visualized. Figure 4(b) is the corresponding slice of the second 3D scan which forms the target to which we wish to match the first volume. Significant sinking of the surface of the brain due to the surgery is apparent. Figure 4(c) illustrates the result of simulating the brain deformation in order to match the first scan to the second scan. A 3D visualization of this match is shown in Figure 5. Figure 4(d) shows the difference between the simulated deformation of the brain of Figure 4(a) and the MRI scan of Figure 4(b) to which it is matched. The closeness of the match of the simulated deformation to the actual deformation can be judged by the very small intensity differences at the boundary of the simulated deformed brain and the air gap inside the skull of the target image. Some small intensity differences are expected because intrinsic MR scanner intensity variability causes a small variation in the observed voxel intensities from scan to scan. A small misregistration of the lateral ventricles on the side opposite the surgical resection can be observed. This occurs because our biomechanical model treats the brain as a homogeneous material, but the cerebral falk (a stiff membrane between the two hemispheres) and the cerebrospinal fluid inside the lateral ventricles are not well approximated by this homogeneous model. This misregistration is not particularly relevant for a surgical resection on the opposite side of the brain.

Figure 5 is a visualization of the simulated deformation of the first intraoperative scan volume onto the second intraoperative scan volume. The 3D surface rendering indicates the simulated deformation of the brain in the first scan and the cross-sectional slices show the MRI of the second scan. The skin appears bright in the MRI, and the large dark region between the skin and the brain surface is part of the deformation due to the surgery. The close match of the simulation and the actual brain deformation is clear. The color coding indicates the magnitude of the deformation at every point on the surface of the deformed volume and the blue arrows indicate the magnitude and direction of the deformation by showing the initial and final position of points on the surface undergoing deformation.

3.2 Performance Analysis of Parallel Implementation

The results here focus upon the biomechanical simulation of brain deformation because in the past obtaining sufficiently accurate results in a clinically compatible small amount of time has been seen as extremely difficult. Often less accurate but fast models of deformation have been used. In order to provide a context for the biomechanical simulation amongst the other image analysis and acquisition tasks that must occur intraoperatively, a timeline for these actions is shown in Figure 6.

Ultimately the ability to use these intraoperative image analysis methods relies upon them being sufficiently robust to provide accurate results for typical clinical cases, and critically, to be sufficiently fast to provide feedback to the surgeon at a rate that can be practical to use during neurosurgery. We collected performance results on three different architectures in order to assess the absolute performance and the scaling behavior of our parallel implementation.
Figure 4: Two dimensional slices through three-dimensional data, showing the match of the simulated deformation of the initial brain onto the actual deformed brain. The quality of the match is significantly better than can be obtained through rigid registration alone. The closeness of the match of the simulated deformation to the actual deformation can be judged by the very small intensity differences at the boundary of the simulated deformed brain and the air gap inside the skull of the target image. Some small intensity differences are expected because intrinsic MR scanner intensity variability causes a small variation in the observed voxel intensities from scan to scan. A small misregistration of the lateral ventricles on the side opposite the surgical resection can be observed. This occurs because our biomechanical model treats the brain as a homogeneous material, but the cerebral falx (a stiff membrane between the two hemispheres) and the cerebrospinal fluid inside the lateral ventricles are not well approximated by this homogeneous model. This misregistration is not particularly relevant for a surgical resection on the opposite side of the brain.
Figure 5: Visualization of deformation of first intraoperative scan volume onto second intraoperative scan volume. The 3D surface rendering indicates the simulated deformation of the first scan and the cross-sectional slices show the MRI of the second scan. The skin appears bright in the MRI, and the large dark region between the skin and the brain surface is part of the deformation due to the surgery. The close match of the simulation and the actual brain deformation are clear. The color coding indicates the magnitude of the deformation at every point on the surface of the deformed volume and the blue arrows indicate the magnitude and direction of the deformation showing the initial and final position of points on the surface undergoing deformation.
Figure 6: A timeline of typical intraoperative image acquisition and analysis tasks.

Figure 7: Timing results for assembling, solving, and the sum of initialization, assembling and solving time for a system of 77511 equations simulating the biomechanical deformation of the brain on a cluster of 16 Compaq Alpha 21164A 533MHz CPU-based workstations networked with Fast Ethernet.
Figure 7 shows the timing results for a biomechanical simulation of brain deformation on the Deep Flow cluster. The simulated deformation determined by solving this set of equations is shown in Figure 4 and Figure 5. This result demonstrates that a biomechanical simulation of volumetric brain deformation can be carried out in less than ten seconds.

The slow scaling of the implementation is attributed to imbalance in the matrix assembly and matrix solve processes. Our parallel decomposition for the matrix assembly is based on sending approximately equal numbers of mesh nodes to each CPU. However, in our unstructured grid different mesh nodes can have different connectivity, and hence require a different amount of work in order to interpolate values to the mesh nodes. A second load imbalance affects the scaling of the solving time. Given an initially balanced set of equations, the surface displacements are applied as boundary conditions, substituting known values for equations in the original system, reducing the number of unknowns that must be solved for. This has the effect of creating some imbalance, as the distribution of surface displacements is not equal across CPUs.

For intraoperative use, the absolute time required for initialization, assembly and solving is acceptable. Time required for initialization can be overlapped with earlier image processing. For display of the simulated deformation we need to resample a data set according to the computed deformation, which requires approximately 0.5 seconds. Our current implementation at this time simply writes the deformation to disk which imposes a fixed I/O cost (not included in the timing results) that will not be necessary in practical application during surgery.

Figure 8 shows timing results for assembling and solving the system of 77511 equations simulating the biomechanical deformation of the brain on a Sun Microsystems Ultra HPC 6000 symmetric multi-processor with 20 250MHz CPUs and on a pair of Sun Microsystems Ultra 80 servers each with 4 450MHz CPUs networked with Fast Ethernet. These results indicate scaling performance similar to that obtained on the Deep Flow cluster, despite the differences in architectures.

In the future an improved biomechanical model could aim to better model different structures in the brain. This may necessitate a higher resolution mesh, and hence a larger number of equations to solve. Figure 9 shows timing results for assembling and solving a system of 253308 equations to simulate the biomechanical deformation of the brain on a Sun Microsystems Ultra HPC 6000 with 20 250MHz CPUs. The timing results indicate that we can assemble and solve a system of equations...
Figure 9: Timing results for assembling and solving a system of 253308 equations simulating the biomechanical deformation of the brain on a Sun Microsystems Enterprise Server 6000 with 20 250MHz CPUs.

2.5 times larger than that necessary to obtain excellent results with our current model in a clinically compatible time frame.

4 Discussion and Conclusion

Our early experience with two neurosurgery cases indicates that our intraoperative biomechanical simulation of brain deformation algorithm is a robust and reliable method for capturing the changes in brain shape that occur during neurosurgery. The registration algorithm requires no user interaction and the parallel implementation is sufficiently fast to be used intraoperatively.

Intraoperative registration adds significantly to the value of intraoperative imaging. It provides for quantitative monitoring of therapy application including the ability to compare quantitatively with a preoperatively determined treatment plan and enables preoperative data to be aligned with the current configuration of the brain of the patient in order to allow 3D interactive visualization of the fused multi-modality data.

The contribution of this work is the evaluation of a parallel implementation of an algorithm for intraoperative registration by biomechanical simulation of brain deformation and the demonstration that high fidelity simulations of brain deformation are not too computationally expensive for intraoperative use. High performance computing is a key enabling technology that allows the biomechanical simulation to be executed quickly enough for the nonrigid registration algorithm to be practical in clinical use during neurosurgery. Our parallel implementation shows a good speedup with increasing CPU count and a wallclock time compatible with the requirements of neurosurgical intervention. We
have evaluated our algorithm with two neurosurgery cases with promising results. Further clinical validation with larger numbers of cases will be necessary to determine if our algorithm succeeds in improving intraoperative navigation and intraoperative therapy delivery and hence improves therapy outcomes.

In the future, the parallel implementation described here could be improved by addressing the load imbalances in order to achieve better scaling performance. A tetrahedral mesh with a more regular connectivity pattern would allow better scaling in the matrix assembly process. The parallel decomposition of the system of equations to solve could be modified to account for the distribution of known displacements in order to improve the scaling of the solver. Improved registration could result from a more sophisticated model of the material properties of the brain (such as more accurate modelling of the cerebral falx and the lateral ventricles). The creation of an intraoperative segmentation capability able to identify these structures would be necessary to enable such a model to be applied routinely in surgery.

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