Automated Brain Shift Correction Using A Pre-computed Deformation Atlas

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ABSTRACT

Compensating for intraoperative brain shift using computational models has shown promising results. Since computational time is an important factor during neurosurgery, *a priori* knowledge of the possible sources of deformation can increase the accuracy of model-updated image-guided systems (MUIGS). In this paper, we use sparse intraoperative data acquired with the help of a laser-range scanner and introduce a strategy for integrating this information with the computational model. The model solutions are computed preoperatively and are combined with the help of a statistical model to predict the intraoperative brain shift. Validation of this approach is performed with measured intraoperative data. The results indicate our ability to predict intraoperative brain shift to an accuracy of 1.3mm $\pm$ 0.7mm. This method appears to be a promising technique for increasing the speed and accuracy of MUIGS.

Keywords: deformation atlas, statistical model, finite element modeling, image-guided surgery, laser range scanning

1. INTRODUCTION

Systematic studies have shown that brain shift, an important phenomena within the field of image-guided surgery, compromises the accuracy of current surgical guidance systems. Also known as post-imaging brain distortion or brain deformation, the shift can be caused by a variety of factors such as surgical manipulation, gravitational forces and pharmacological responses. One important statistically significant finding common to most brain shift studies is that the direction of brain shift has a predisposition to move in the direction of gravity.[1]

To correct for deformations, various imaging techniques such as computed tomography (CT),[2] magnetic resonance imaging (MRI),[3] and ultrasound (US)[4] have been used for intraoperative image-guided surgery. CT procedures have been questioned for their dose exposure, while MR procedures are labeled cumbersome and have been questioned for their cost-effectiveness. Current US systems suffer from low signal-to-noise ratio and lack the image clarity that CT and MR scans produce. Therfore in their current state, intraoperative imaging systems do not present a complete solution for corrective guidance of the brain shift phenomenon.

As a cost-effective and efficient method, computational modeling is a procedure that can translate complex surgical events into accurate estimates of tissue response and thereby compensate for intraoperative brain shift. In model-updated image-guided neurosurgery (MUIGNS), a biomechanical model of brain shift is driven with

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sparse data (i.e. data with limited intra-operative extent or information) to accurately deform pre-operative images to their current intra-operative position. For example, Miga et al. demonstrated the full model updates of a tumor resection, retrospectively.[5] While these results were encouraging, the time required to generate model solutions was still somewhat long for real-time use.

In order to potentially improve the efficiency and accuracy of the calculation, a statistical model was combined with the computational model and preliminary results were presented in.[6] The work presented here extends the framework developed by Davatzikos et al[7] by incorporating elements of principal component analysis (PCA). In addition, an algorithm was developed for the automated generation of multiple sets of boundary conditions in order to facilitate the pre-computation of a "statistical deformation atlas" of solutions. The combined approach is tested using data from an *in vivo* case where measurements of brain shift were acquired using an optically tracked laser range scanner (LRS).[8]

2. METHODS

2.1. Computational Modeling

This section briefly discusses the computational model used in this study. Equations 1 and 2 were used by Paulsen et al[9] to model the deformation behavior of brain tissue.

$$\nabla \cdot G\nabla u + \nabla \frac{G}{1-2\nu}(\nabla \cdot u) - \alpha \nabla p = -(\rho_t - \rho_f)g \tag{1}$$

$$\alpha \frac{\partial}{\partial t}(\nabla \cdot u) + \frac{1}{S}\frac{\partial p}{\partial t} - (\nabla \cdot k\nabla p) = 0 \tag{2}$$

First reported within the context of gravity-induced brain shift by Miga et al,[10] the right-hand-side of Equation 1 is used to represent the change in buoyancy forces that can occur in the event of cerebrospinal fluid loss from the cranial cavity. The above partial differential equations were solved using the finite element method. A more detailed development of the equations and their solutions can be found elsewhere.[9,10] Briefly stated, the model is a porous-media model in which the elastic matrix obeys the laws of a Hookean solid and the interstitial fluid dynamics flows in accordance to Darcy's law.

2.2. Automatic Boundary Condition Generator and Atlas Formation

In order to predict intraoperative brain shift using the statistical model based on a pre-computed deformation atlas, a number of training samples/displacement data sets are required. Additionally, for increased accuracy of the statistical model, it is important that the model represent the degree of uncertainity associated with all the sources of deformation. For example, a statistical atlas for predicting gravity-induced brain deformations should contain displacement data sets for a range of possible patient orientations in the operating room(OR) and varying degree of buoyancy forces for each patient orientation. The surgeon's preoperative plan can be used to approximate the patient's orientation in the OR and subsequently used to generate multiple boundary condition (BC) sets, to sample all possible patient orientations. This underscores the need for a template BC that is accurate so as to facilitate automatic BC generation.

Based on the BC representation reported by Miga et al,[10] a patient-specific automatic boundary condition generator has been developed. The only necessary inputs are the approximate patient orientation in the OR as predicted by the neurosurgeon's preoperative surgical plan, the computational mesh based on the preoperative image volume, and the location of the patient's brain stem in the preoperative image study. Based on this information, all possible patient orientations in the OR are assumed and BC sets for the patient-specific mesh domain are generated. The automatic BC generator algorithm is as follows:

1. For a given patient orientation, the node normals for all nodes on the boundary are calculated and the following operation is performed over all boundary nodes : $e_g \cdot e_{n_i} \leq \epsilon$, i = 1,2,3,...,$N$ boundary nodes, where e_g is the gravitational unit vector and e_{n_i} is the unit vector associated with the nodal normal to the brain surface for the i^{th} boundary node, and ϵ is a tolerance specified by

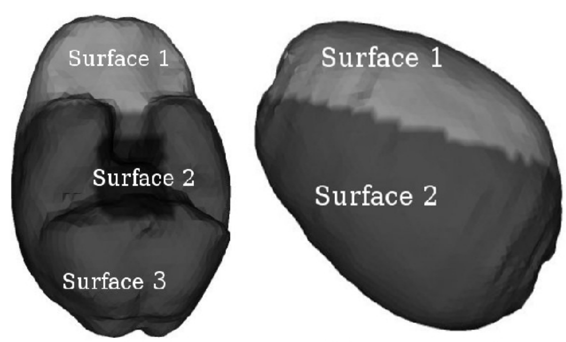
the user *. Boundary nodes that satisfy this condition are assigned stress-free boundary conditions (Neumann condition), while those that do not satisfy are allowed to slide along the cranial cavity but not in the direction of the surface normal.

2. The brainstem is identified from the patient's preoperative images and nodes within a given radius are classified as fixed (Dirichlet condition), which overrides the conditions determined in Step 1.

3. The interstitial pressure BCs are determined by: $d_i \cdot (-e_g) \geq h_j; h_{min} \leq h_j \leq h_{max}$, j = 1,2,3,. . . ,$M$ elevations, where d_i is the Cartesian coordinate of the i^{th} boundary node and h_j is an elevation distribution. The upper (h_{max}) and lower bound (h_{min}) for the elevation distribution are determined from our previous experiences in the OR. Boundary nodes that satisfy the above expression are considered to be at atmospheric conditions (Dirichlet condition), while those that do not satisfy are the non-draining regions of the brain (Neumann condition).

4. Elements in the domain with reduced buoyancy forces are identified based on the following expression : $D_k \cdot (-e_g) \geq h_j; h_{min} \leq h_j \geq h_{max}$, j = 1,2,3,. . . ,M elevations, where D_k is the Cartesian position of the k^{th} tetrahedral element centroid. Elements satisfying this condition are considered to have a complete reduction in their buoyancy forces and are assumed to have a surrounding fluid density equal to that of air (ρ_f as shown in Equation 1). Elements that do not satisfy the above condition are assumed to have a surrounding fluid density equal to that of the tissue density (ρ_t as shown in Equation 1).

The template boundary condition used to develop the automatic boundary condition generator is illustrated in Figure 1. For the BC set shown here, the patient was supine and the head was turned approximately 60° to the patient's left.



(a) BC template for neutral head orientation in the OR.

(b) BC template for patient's head turned 60° orientation in the OR.

Figure 1: Surface 1 is stress-free at atmospheric pressure; surface 2 slides along the cranial wall but not along the normal direction and surface 3 is fixed for displacements. The amount of intraoperative CSF drainage determines the drainage boundary condition.

2.3. Statistical Model

As discussed above, computational time is an important factor in MUIGNS. *A priori* knowledge about the sources of deformation can improve the efficiency and accuracy of a MUIGNS system. For example, in the biphasic model, the patient's orientation in the OR and the amount of intraoperative CSF drainage are two

*The authors found that a threshold value between -0.2 and -0.3 worked best for all patient orientations

factors governing the effect of gravitational forces on the brain.[6,10] Although the preoperative surgical plan can provide an estimate of the patient's orientation *a priori*, estimates for the degree of change in buoyancy forces acting on the brain are somewhat more elusive.

As a result, equations (1) and (2) are solved for a range of possible brain shifts due to the influences of orientation and buoyancy force reduction. Let **E** be the matrix obtained by assembling these model solutions. This statistical atlas is computed prior to the surgery. The matrix **E** will be of size N $\times$ M, where N is the number of nodes in the finite element mesh and M is the number of model solutions. In general, N does not equal M, so **E** is a rectangular matrix. The model solutions in **E** are then interpolated to the intraoperative data points and these interpolated solutions are assembled in the intraoperative atlas, **I**. The displacement data sets in **I** serve as the training samples for the statistical model. The intraoperative brain shift is predicted by examining the statistics of **I**. Our assumption is that the model solutions in **E** and therefore the solutions in **I**, follow a multivariate Gaussian distribution, with density *f(I)* that is parameterized by its mean μ_I and its covariance matrix $\mathbf{C_I}$. Any displacement data set in **I** can then be parameterized as follows:

$$x_I = \mu_I + V_I \alpha \tag{3}$$

where x_I is the shape of the cortical surface, V_I is a matrix containing the eigenvectors of C_I and α is the vector of interpolating coefficients. It can be shown that the eigenvectors of the covariance matrix corresponding to the largest eigenvalues describe the most significant modes of variation in the displacement data sets used to create the intraoperative atlas.[11] Eigenvalues and the corresponding eigenvectors pairs are chosen, such that they represent most of the variation. Equation 3 can therefore be rewritten as :

$$x_I = \mu_I + V_I' \alpha_t \tag{4}$$

where V_I is the matrix of eigenvectors associated with the first t largest eigenvalues. The measured intraoperative data is used to constrain the statistical model and to find the vector α which minimizes the objective function

$$\epsilon(\alpha) = \|x - x_0\|^2 = \|\mu_I + \sum_{i=1}^{t} \alpha_i v_i - x_0\|^2 \tag{5}$$

where x_0 is the measured intraoperative displacement. The above term seeks vectors that get as close as possible to the patient's measured intraopertive displacements. Let these vectors be expressed as $\alpha_t = [\alpha_1, \alpha_2, \ldots, \alpha_t]^T$. Using these interpolating coefficients, the full volume displacement field is given by:

$$X = \mu_E + V_E' \alpha_t \tag{6}$$

where X is the volumetric shift, μ_E is the mean shape of the statistical atlas **E**, V_E' is the matrix of the dominant eigenvectors of the covariance matrix of **E** and α_t is the vector of interpolating coefficients obtained from Equation 5. It should be noted that V_E and V_I are precomputed and therefore most of the computations are preformed preoperatively.

2.4. Experiment

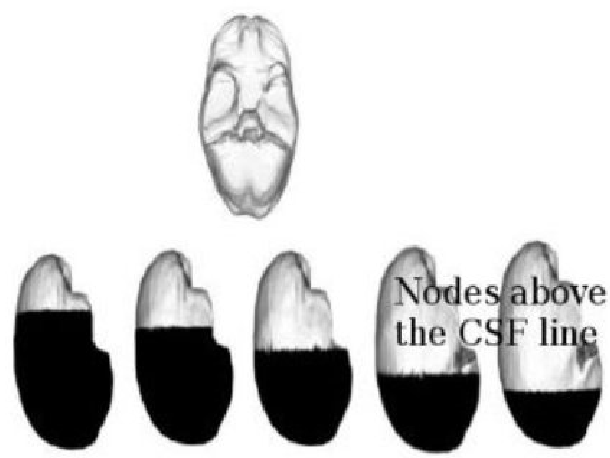
In the recent work by Sinha et al.,[8] a laser-range scanning(LRS) device was used to capture the cortical surface before and after tumor resection. These acquired LRS surfaces were then registered to the physical space and were used to determine the brain shift over the course of the entire surgery. Corresponding points were identified on the two serially tracked LRS surfaces by a surgeon and brain shift was calculated as the difference in position between the two points. A patient-specific model was created, automatic BC generation was performed, and three separate deformation atlases were computed: (i) the tumor was assigned the same stiffness properties as normal brain tissue (ii) the tumor was assumed to be 10 times stiffer than the brain tissue,[5] and (iii) the tumor was assumed to be resected from the volume. Tissue resection was simulated by identifying the model elements that coincide with the preoperative tumor volume and decoupling the corresponding nodes.[5] For each atlas, 27 different patient orientations with 4 different elevations for each orientation were used resulting in a total of 108 displacement data sets/training samples for the statistical model. The brain shift measured using LRS (x_0

in Equation 5) was used to constrain the statistical model and the interpolating coefficients were determined. The predicted intraoperative shift was then compared against the measured intraoperative shift. Directional accuracy of the predicted shift is also reported as a measure of the angle of deviation(θ) formed between the predicted and measured shift vectors. The results for all three atlases are presented in the following section.

3. RESULTS

Figure 2(a) shows a sampling of the BC atlas as generated by the automatic BC generator algorithm for the displacement/stress BCs. Figure 2(b) shows a sampling of the BC atlas for the interstitial pressure BCs.

(a) Sampling of the BC atlas as generated by the automatic BC generator algorithm for the displacement/stress BCs



(b) Sampling of the BC atlas for the interstitial pressure BCs.

Figure 2: BC sets developed by the BC generator algorithm

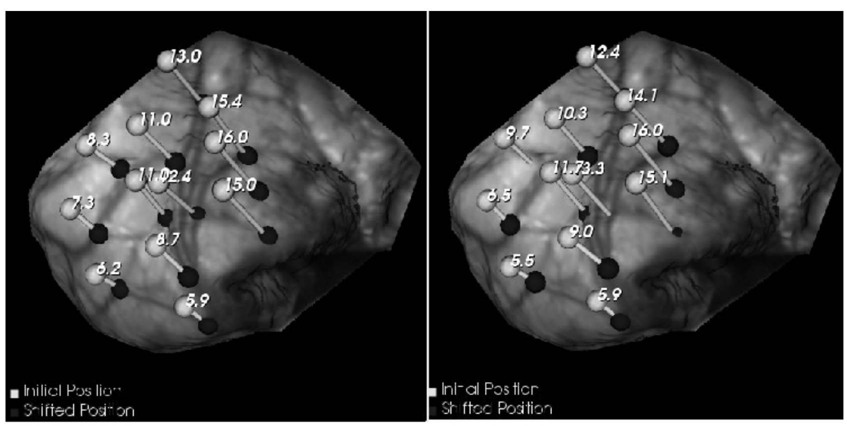
Table 1 shows the error between the predicted and the measured intraoperative brain shift, for all three scenarios. Shift error in the table refers to the error in the magnitude between the measured and the predicted

True Shift(mm)	Error	Case I		Case II		Case III	
		Shift Error (mm)	θ Error (°)	Shift Error (mm)	θ Error (°)	Shift Error (mm)	θ Error (°)
16.3	Max	2.9	13.2	3.4	13.8	2.2	13.2
5.7	Min	0.2	1.6	0.7	1.6	0.3	0.8
10.8	Mean	1.3	5.6	1.6	6.6	1.3	5.5
3.7	σ	0.7	3.9	0.9	3.8	0.7	3.7

Table 1: Shift Error and Angular(θ) Error between the measured and predicted intraoperative brain shift. Case I : Tumor was modeled as "normal brain" tissue. Case II : Tumor was assumed to be stiffer than brain tissue. Case III : Tumor resection was modeled. σ refers to the standard deviation.

intraoperative brain shift, while angular error represents the directional error between the measured and the predicted intraoperative brain shift. When the tumor was modeled as "normal brain", a mean shift error of 1.3mm±0.7mm with a mean angular deviation of 5.6° ± 3.9° was observed. When the tumor was assumed to be stiffer than the brain parenchyma, a mean shift error of 1.6mm±0.9mm, with a mean angular deviation of 6.6° ± 3.8° was observed. For the tumor resection, a mean shift error of 1.3mm±0.7mm, with a mean angular deviation of 5.5° ± 3.7° was observed.

In order to visualize the shift vectors (shown in Figure 3), the measured and predicted shift were added to the initial position and were projected on to the LRS surface acquired after resection.



(a) Measured Shift (b) Predicted Shift

Figure 3: Measured (upper left) and predicted shift vectors (shown as line segments) overlaid on the post-resection LRS surface.

4. DISCUSSION

The goal of this work is to achieve comparable or improved accuracy in matching model predictions to the measured intraoperative displacement, using a statistical model. The statistical model accounts for 85-88% of the average shift and 79-87% of the maximum shift. 12 corresponding points were used to calculate the intraoperative brain shift and were used as measured intraoperative data. To increase the accuracy, simulations suggest that dense intraoperative cortical shift measurements may be appropriate.[6,12] In related work, efforts are underway to automate the shift tracking process using LRS such that dense shift measurement points of the cortical surface will be available.[8] Despite the admittedly sparse data field used for constraining the statistical model, these results are encouraging. In addition to shift due to gravitational sag, one advantage to the model

in Equations (1) and (2) is its ability to simulate other complex loading conditions such as mannitol-induced volume reduction or tissue swelling. It would be interesting to add these conditions to our statistical model and compare results to measured intraoperative data.

5. CONCLUSIONS

Given the complex surface (e.g. retraction) and volume loading conditions (e.g. sag, mannitol) possible within the OR, the integration of sparse intraoperative data into a finite element model is not a trivial problem. Recognizing this challenge, a strategy for estimating brain shift from pre-computed model solutions is presented which takes advantage of information that can be determined from the preoperative surgical plan. When combining this approach with sparse data acquisition methods such as laser range scanning, the results suggest that we can achieve effective estimates of measured cortical brain shift. The next goal is to take this approach and assess accuracy for deformation volume updates.

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