INTRAOPERATIVE NEUROIMAGE COMPENSATION USING DATA DRIVEN COMPUTATIONAL MODELS

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ABSTRACT

Loss of coregistration between preoperative imaging studies and the surgical field due to brain deformation during surgery is an important problem that has recently received considerable attention. Methods for compensating or correcting for the loss of congruence between image and surgical views are taking a variety of forms and involve a spectrum of data acquisition techniques (range from re-imaging with MR to point-tracking through cortical surface digitization) and/or image processing schemes (ranging from non-rigid registration to biomechanical modeling). This paper describes an emerging approach to intraoperative image compensation which combines pre- and intraoperative data acquisition with computational biomechanical modeling to estimate full volume deformation distributions that result from neurosurgical interventions. The strategy updates preoperative scans by projecting this displacement estimation onto the coregistered imaging study to deform it into a new image volume which reflects the geometrical changes in the surgical field which have occurred during surgery. Discussion and summary of developments associated with this idea which have appeared in the recent literature are presented.

1. INTRODUCTION

Conventionally, image guidance in neurosurgery has involved a preoperative image volume rigidly registered to the intraoperative space through digitization of common points of reference (fiducials) in the operating room (OR). These points are co-located in the image volume to create intraoperative views that are aligned with the OR reference frame in order to provide a source of information for navigational guidance. It is now widely recognized that new approaches to image guidance are needed which incorporate some form of image compensation to update the preoperative image volume in a way that more accurately reflects the conditions concurrent with surgery than the original, rigidly registered preoperative scans. This paper will focus on one such strategy which exploits biomechanical models as the vehicle for presenting coregistered image views that have been deformed based on OR events. Five questions will be considered, namely: (1) What models are available? (2) What kind of information do these models require? (3) Where will this information come from? (4) How will models use the information? and (5) How well do current models work?

2. WHAT MODELS ARE AVAILABLE?

The biomechanical models which have appeared in the literature to date for intraoperative image compensation of brain deformation can be categorized as semi-discrete or continuous. In the semi-discrete class both compartmental and spring-mass systems have been considered. Perhaps the first compartmental approach to be reported was the three-component deformation model described by Edwards et al.[1] In this work the three components were designed to include the rigidity of bone, the unconstrained characteristics of cerebrospinal fluid (CSF) and the generally smooth displacement of soft tissue by compartmentalizing these three zones within the image volume. Rigid body transformations were applied to bone, fluid volumes were left unconstrained and soft tissue zones were modeled with various energy terms (e.g. tension, stiffness, spring, etc.) of which a stiffness plus tension combination appeared to produce the best results in the example case illustrated. Skrinjar and Duncan[2,3] have reported the largest experience with spring-mass systems for brain deformation modeling. In their work, the brain was represented as a coupled set of second order ordinary differential equations describing the dynamics of an interconnected set of spring-dashpot mechanical elements. Typically, mesh node systems on the order of several thousand equations have been solved. As described in more detail later in this paper, the technique has been applied to several clinical examples where the location of points on the cortical surface have been tracked during the course of surgery with a mechanical digitizer and compared with model estimates of the motion.

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In the continuum model class linear elasticity, consolidation and viscoelasticity have been explored as frameworks for image compensation due to brain deformation in the OR. Examples of linear elastic biomechanical models have been reported by several investigators[3,4-6]. In these studies, the finite element method (FEM) has been used to solve the classical partial differential equation description through discretization of the anatomy into an inter-connecting set of nodes and elements on which discrete forms of the continuum equations are assembled into a coupled linear algebraic system whose solution is achieved through standard matrix methods. Both 2D and 3D model geometries have been considered and a number of clinically motivated case examples have been described. A significant advantage of the FEM approach is its ability to represent heterogeneous and geometrically-complex volumes such as the brain. Consolidation physics has been developed in the context of brain deformation modeling for image compensation as well.[7,8] Consolidation is a process initially explored in soil mechanics which has been adapted to the biomedical arena. It is a biphasic description suitable for a porous-medium consisting of an elastic skeleton permeated by an incompressible fluid. In the setting of brain tissue mechanics, the pore fluid is represented through a pressure field surrogate whose spatial gradient becomes a driving force for tissue deformation. The pressure field distributes in accordance with Darcy's law and is dependent on the hydraulic conductivity of the tissue. The consolidation approach is an attempt to recognize the important role that fluid and/or pressure play in modulating the deformation response of the brain as an elastic continuum.

In related methods, Hagemann et al.[9] have recently reported an effort to couple rigid, elastic and fluid regions within the brain (in the spirit of Edwards et al.[1]) by using separate physical (and continuum) descriptions in these respective regions, namely, the Navier equation (i.e. linear elasticity) in the soft tissue and the Stokes equation (i.e. for incompressible fluids) in the regions of CSF. This contrasts with the consolidation model strategy which eliminates zones of CSF (e.g. ventricular system) and represents the interstitial fluid compartment through a pressure field. In the Hagemann approach regions of CSF are segmented explicitly and Stokes model equations are enforced in the portions of the FEM mesh which represent these volumes. Critical, then, become the interface conditions applied between the elastic solid and CSF-fluid zones. The method has been evaluated on several 2D synthetic and tomographic images and found to produce more realistic deformation fields than a single compartment elasticity model.

An interesting series of model developments have been reported by Miller and colleagues.[10-12] This work describes a viscoelastic approach to deformation modeling of the slow strain rate processes involved in the mechanical events which take place during surgery. The model has been motivated by the observation that biphasic soft tissue theories do not account for stress-strain rate dependencies which may be important during surgery.[11] Specifically, these investigators have argued that the ratio of instantaneous stress (after sudden movement) to equilibrium stress (after the load has been applied for some time) cannot exceed 1.5 in biphasic models, which places upper bounds on the stress dependency of loading velocity.[13] While experimental studies are cited where the conditions investigated produce ratios in excess of 1.5, there are no direct measurements obtained during typical neurosurgical procedures to suggest that loading velocity is a critical concern. The Miller model is developed around a constitutive equation of polynomial form with time dependent coefficients requiring four material parameters to be determined. Model predictions have been compared with in vivo data obtained in the porcine brain during indentation experiments and show computed force-displacement curves very similar in shape to experimental results but with predicted forces about 30% lower than their corresponding experimental values.

3. WHAT KIND OF INFORMATION IS REQUIRED?

The computational models described in the previous section require several forms of data. Specifically, the anatomical geometry is critical because the shape of the brain and its constituent components are important determinants of mechanical response to surgical loads. Clearly, the mechanical properties of the parenchyma and other cranial structures, for example, the falx, are also important factors which influence the complexity and extent of brain deformation induced during surgery. Boundary and driving conditions are typically the most sensitive model inputs in terms of being capable of exerting the largest effect on the computed displacement fields. Further, boundary and forcing behaviors can be difficult to represent in situations where complex interactions take place and are often expressed through equivalent or effective parameterizations which mimic observed responses but do not necessarily model the small-scale interactions that actually occur.

To illustrate some of the issues involved consider the cranial walls. On the one hand the bone provides a rigid structure which essentially prevents any outward soft tissue motion, although the parenchyma may slip along the rigid walls depending on the local forces at play. This type of displacement (no normal but tangential motion allowed) is common in mechanical modeling and relatively straightforward to implement. On the other hand, during surgery the parenchyma may pull away from the cranial wall in some locations and this motion must be allowed, creating a contact problem which results in boundary conditions that are much more difficult to implement. Further, the dura is not necessarily removed over some portions of the cortical surface where contact with the cranial vault is not maintained, creating a free surface that is not likely stress-free because of the lateral tension supplied by an intact dura which is difficult to quantify. In sum, a significant amount of uncertainty exists in applying boundary and forcing conditions during surgery that will need to be investigated further as biomechanical models mature. Fortunately, for the most part, reasonable approaches do exist for representing the dominant, first order effects that will likely become refined as understanding improves over time.

4. WHERE WILL THE DATA COME FROM?

Fortunately, there are several existing and emerging sources of both preoperative and intraoperative data that are likely to offer rich supplies of information for biomechanical modeling of brain deformation during surgery. Conventional preoperative MR imaging is already routinely available and capable of providing subject-specific anatomical geometry and tissue-type heterogeneity (e.g. gray versus white matter). The majority of continuum mechanics models described in Section 2 exploit finite element technique to effect their solution. As noted, the FEM scheme is particularly attractive in this setting because of its ability to accommodate complex geometries and material type heterogeneities. Several excellent examples of patient-specific, three-dimensional finite element meshes (computational geometries) generated from preoperative MR image volumes have been reported.[5,6,14] The process in generally a multi-step procedure beginning with segmentation of the brain parenchyma in the preoperative MR followed by volume rendering of the binary image to create a mask from which a surface description is generated with marching cubes. The marching cubes surface is typically decimated and smoothed in a volume-preserving manner to create a surface tessellation that captures the overall shape of the segmented parenchyma without over-representing cortical gyral/sucal patterns which are too small scale for current brain models to resolve in a computationally efficient manner.

Once the final surface has been generated, a volumetric meshing algorithm fills the intervening space with finite elements which are typically tetrahedral volumes of one or more millimeters in length on a side. One advantage of finite element meshing is that gradation in element size can be readily accomplished and exploited. For example, tetrahedral elements in the area of preplanned surgical intervention can be millimeter (or less) in scale while portions of the brain not in the immediate surgical focus (e.g. contralateral hemisphere) can be resolved at length scales of 5 mm or more depending on characteristics of the local geometry and tissue heterogeneity. This feature of non-uniform meshing affords important flexibility if biomechanical models are anticipated to become interactive in the OR.

There are several strategies for creating heterogeneity within the model. One approach creates an image-to-grid segmentation. This technique first creates the FEM volume mesh as previously described and then averages the MR voxel intensities that reside in each tetrahedral element and encodes the element tissue type according to a predefined MR intensity to tissue-type correspondence map. The approach is simple to implement and generally very effective provided the voxel-to-element ratio is not too far from unity. A second approach exploits a multiple material marching cubes concept[15] where tissue structure/substructure segmentations are created in the original MR image volume from which surface tessellations are created that become defining boundaries to be obeyed during the volume mesh generation process. Readily identified structures such as the ventricular system and the falx have been handled in this way. To date, fine delineation of gray-white matter boundaries has proved to generate FEM meshes which are too large for computations expected to occur in the OR.

Other sources of preoperative data include specialized MR sequences which may yield important information on subject-specific tissue properties. For example, diffusion tensor imaging (DTI) and magnetic resonance elastography (MRE) offer exciting possibilities in this context. In the case of DTI, it is plausible to project that heterogeneity and anisotropy in tissue parameters such as hydraulic conductivity may be obtainable. This would allow property value delineation between gray and white matter while also supplying geometric information on preferred direction and strength of fluid flow along white matter tracks. Anisotropy maps based on DTI are readily available in humans but translating this information into tissue constitutive properties related to fluid flow or pressure propagation remains to be developed. A recent study in the porcine brain was reported where DTI information was incorporated into consolidation theory modeling to define heterogeneous and anisotropic hydraulic conductivity based on an empirical dimensional-argument mapping between diffusion and conductivity. The results showed modest improvements in model estimates relative to in vivo measurements of brain deformation with the largest amounts of the improvement resulting from incorporation of heterogeneity rather than anisotropy.[16] The preferential geometry associated with fiber tracking obtained through DTI may also yield information that would be relevant to implementation of mechanical property anisotropy. While it is difficult to rationalize the use of DTI to determine anisotropic mechanical property values based on the diffusion of water per se, it does seem plausible that the directional information obtained would correspond to expected directions for mechanical property anisotropy.

Mechanical properties of the brain may also be determinable from the emerging technique known as magnetic resonance elastography (MRE).[17,18] MRE exploits phase contrast techniques to encode mechanical wave motion delivered by direct stimulation of the tissue of interest by some form of mechanical actuation. To date, the majority of research studies investigating MRE have assumed that the tissue being imaged is mechanically isotropic and generally, linearly elastic. Much of the activity has been targeted at breast cancer detection but there has been some work in the brain which has reported results from in vivo human studies. Intersestingly, the literature contains a relatively modest amount of information on brain tissue mechanical properties and what does exist is not completely consistent. For example, Nagashima and Basser[19,20] have suggested that gray matter is stiffer than white by approximately two-fold with shear modular values in 1-3 kPa range, whereas the recent in vivo data from MRE has indicated that white matter is stiffer than gray by 2-3 times with values of white matter reaching 14 kPa (and gray matter 5.3) on average.[21-23] Interestingly, the MRE data for average gray and white matter values is relatively consistent across age (spanning 20-80 years) and standard deviations for the two tissue classes (i.e. gray and white) generally do not overlap, suggesting a statistically significant difference in elasticity between gray and white matter in the 20 normal volunteers imaged.

In addition to preoperative imaging, intraoperatively-acquired data offers an important source of information for biomechanical modeling. Boundary data can be obtained from the cortical surface using point or image-based instrumentation. Movement of surface points – for example, vessel junctions – can be recorded with optically or mechanically tracked stylus probe digitizers. Image views of the surgical field can be coregistered through camera systems mounted to the operating microscope or by scanning laser range finding systems. This information can be incorporated into biomechanical models as boundary data which is used to drive model updates. Examples include point tracking of cortical surface features over time during surgery as reported by Skrinjar[2,3] and binocular stereo recording and extraction of the cortical surface which can differentiate a sagging from bulging surface and even the pulsations of the surface in synchrony with the heart beat as described by Sun.[24] Accuracies in feature localization and registration based on stereo-pair surface views have been on the order of 1.5 mm in these preliminary studies.

In addition to the cortical surface for use as boundary data in biomechanical models of brain deformation, the subsurface provides a rich environment from which to develop forcing constraints for modeling purposes. In this setting, coregistered intraoperative ultrasound (US) becomes an excellent tool for determining partial volume deformation of readily visible (with US) structures such as the ventricles, falx, solid tumors and sulci, among others. A number of recent studies have shown that the accuracy of coregistered ultrasound is sufficient for subsurface tracking of surgically induced deformation. Comeau and colleagues[25] reported some elegant phantom studies which represented soft tissue (parenchyma) with simulated ventricles. A variety of registration and deformation experiments were performed which demonstrated that homologous points between preoperative scans and intraoperative ultrasound could be mapped with an accuracy of better than 2 mm. Tronnier et al.[26] investigated the coincidence of lesion detection and resection boundaries in intraoperative MR (iMR) versus intraoperative US (iUS). They concluded that iMR was superior to iUS in terms of resection control, although the real-time arbitrary orientation of iUS scanning made it a very attractive alternative. Lunn et al.[27] reported that coregistered iUS sweeps can be used to recover tissue displacements induced in the porcine brain during deformation experiments with an accuracy of 1 mm despite absolute registration errors of approximately 1.5 mm. This work has progressed to the OR where coregistered iUS sweeps are routinely overlaid with preoperative MR in order to estimate subsurface tissue motion during surgery.[28]

5. HOW TO USE PREOPERATIVE AND INTRAOPERATIVE DATA?

As noted in the previous section, preoperative MR scanning can be used to develop subject-specific computational domains based on the patient's anatomy. It can also be used in either conventional or specialized forms to generate structural heterogeneity and possibly tissue mechanical and hydrodynamical property maps on a subject-specific basis. The more challenging and open-ended question is to determine the possible and optimal strategies for incorporating intraoperatively-acquired data as modeling constraints which improve the accuracy with which modeling methods can be used to accomplish preoperative image updating. To date, several ideas have emerged, although a significant amount of work remains to be completed before optimal schemes will become evident.

Of the available options considered to date, direct application of intraoperative data as displacement or normal stress boundary conditions appears to be a logical choice. Other alternatives would include some form of volumetric or distributed forcing, for example, as in gravitational sagging or some other type of volumetric sink or source in the displacement or pressure fields. Excellent examples of direct application of intraoperative surface information as boundary data can be found in several recent studies[3,6]. In collaboration with the Surgical Planning Laboratory at Harvard, the Yale group reported a surface-guided deformable brain model where surface maps acquired intraoperatively drove the brain model to generate intraoperative updates of the preoperative MR which were compared to iMR images. Ferrant completed similar analyses showing surface driven model updates in comparison to interventionally obtained surgical MR.

While direct application of surface motion as model displacement boundary conditions is appealing, it may not represent the best alternative. As described by Miga et al. and further developed by Lunn and collaborators, enforced displacement on the model boundary generates a surface stress that likely does not exist.[29,30] Further, when the effect of the displacement of the surface is resultant from a volumetric or distributed phenomenon such as gravitational sagging due to loss of buoyancy, a surface displacement boundary condition significantly underestimates the subsurface deformation. This is not surprising because the effect of the surface displacement boundary condition is localized near the point of application rather than distributed throughout the volume.

Other strategies for incorporating intraoperative data as model constraints include the weighted basis solution technique[31] and data assimilation by representers.[30] The weighted basis solution scheme pre-computes unit driving conditions for expected neurosurgical events, for example, gravitational sag, tissue retraction, tissue pressure localization, etc., and synthesizes linear combinations of these basis solutions which match the observed data in a least squares sense. This scheme has been implemented and evaluated in a preliminary fashion using intraoperative CT images acquired during localized retraction experiments in the porcine brain. The results showed that including some intraoperatively-acquired point displacements as matching conditions for gravity, retraction and pressure basis solutions was superior to model estimates obtained in the absence of any intraoperative constraints.

Data assimilation by representers minimizes the model data misfit (weighted by a data error covariance matrix) by constructing an objective function which also restricts the size of the forcing vector while simultaneously enforcing the model equations through a Lagrange multiplier. In effect, the displacement fields generated by a unit error at each of the observation points are combined subject to the size weight and model equation constraints in order to yield an optimal solution. In a 2D example of this technique, Lunn and coworkers[30] showed that the method can be effective. They performed a retrospective analysis involving coregistered iUS tracking of a ventricular surface as the observable for data assimilation through the representer methodology. The updated preoperative MR matched the intraoperatively acquired ultrasound overlay once deformed with the modeling scheme.

6. HOW WELL DO MODELS WORK?

Validation of biomechanical models for intraoperative neuroimage updating is only beginning to appear. A number of animal model and human studies have been reported over the last several years. Much of the clinical work has been retrospective, although analyses performed in the OR are beginning to appear. In the case of animal studies, typically intraoperative full volume scanning has been available for evaluating model estimation accuracy. Deformations induced have involved relatively simple compression or indentation forces, although some retraction studies involving a retractor blade interhemispherically inserted have been described.[32] In these as well as the clinical case analyses completed to date, intraoperative imaging has played an important role.

The human studies reported in reference 3 where intraoperatively-acquired surface data was incorporated as displacement boundary conditions showed maximum displacement errors of 1.3-1.4 mm in two clinical cases where iMR was available to compare model estimates. These surgeries were not particularly invasive as the maximum displacements in each case were less than 4 mm overall. Nonetheless, the better than 1.5 mm accuracy using a model to update preoperative scans is very encouraging. Similar findings have been reported in reference 6. In this work, surface deformations from iMR at 4 time points were used as boundary conditions for model computations. The iMR validations showed that the model updates of the preoperative MR differed on average by 1 mm at 400 selected points and reduced the maximum difference between locations in the pre and intraoperative scans from 7.2 mm to 2.6 mm. The results are also very encouraging and suggest that the model updating approach may prove to be very effective in practice provided the methods for incorporating intraoperative data and computing the resultant full volume displacement field can be optimized through future studies.

The group at Dartmouth recently presented model updates of gravitational sag in the OR concurrent with surgery.[28] This is an important step forward in terms of acquiring the necessary data both preoperatively and intraoperatively, to construct the model, register it with the surgical field, compute the model update and project the deformation field onto the preoperative MR to present an updated view to the surgeon in the OR. In this study, data from a stereo-pair of images reconstructing the cortical surface were used to define the craniotomy. After sag, the model updated MR was compared with the projection of a stylus probe acquisition of a vessel junction into the OR coordinates of the spatially registered operative field and found to align with the computational estimation.

7. CONCLUSIONS

Model based intraoperative updating of preoperative MR scans to improve neuronavigational guidance is an attractive concept which presents a number of challenges in terms of (i) the underlying model equations, (ii) the model construction and tissue property parameters needed for its execution, (iii) the intraoperative data that can be acquired to guide and constrain the model predictions and (iv) the means and methods for incorporating this information into the model updating process. Given the significant progress in each of these areas which has occurred over the last few years, one can anticipate that image compensation through modeling methods will become more routine in the future. Certainly, the validation of these methods is crucial and will ultimately determine their utility in this setting. Initial validation studies in animals and more recently in humans have begun to appear but these only represent the beginning of the overall effort required to establish the modeling methodology as clinically viable. Computational overhead is another important issue for future investigation since model updates concurrent with (rather than retrospective to) surgery are essential for the technique to be successful.

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