

Haptic-Assisted Brain Surgery from a CT Scan

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ABSTRACT

This paper presents a theoretical and conceptual framework for haptic-assisted brain surgery based on patient-specific computed tomography (CT) imaging. CT-derived anatomy and radiodensity are used to construct a patient-specific three-dimensional computational domain, while brain mechanical properties are identified through biomechanical measurements and inverse modelling rather than inferred directly from CT intensity. The framework integrates nonlinear viscoelastic brain mechanics with thermomechanical modelling to predict deformation, stress, brain shift, temperature and tissue-damage risk when thermal instruments are used. Model-predicted interaction forces and safety indicators are then translated into visual and haptic cues to support surgical planning and haptic-guided operation. The proposed approach is expected to provide quantitative measures of tissue-property estimation error, registration error, deformation and force prediction errors, peak interaction force and trajectory deviation. By linking patient-specific imaging, biomechanical identification, computational prediction and haptic rendering, the framework aims to transform static preoperative imaging into a dynamic mechanics-informed representation for neurosurgical planning, simulation and future robot-assisted intervention. Clinical translation will require further validation, uncertainty management and low-latency computational implementation.

Keywords: Brain Surgery; Computed Tomography; Patient-Specific Modelling; Brain Shift; Inverse Biomechanics; Thermomechanical Modelling; Haptic Feedback; Surgical Robotics

Introduction

Brain surgery requires exceptionally high precision because lesions are frequently located close to functionally critical cortex, white-matter pathways, vascular structures and deep-brain nuclei. Small errors in target localisation or excessive instrument-tissue force can therefore affect surgical accuracy and increase the risk of unintended injury. Modern neurosurgery has consequently moved toward image-guided navigation, patient-specific three-dimensional (3D) modelling, simulation and robotic assistance to improve spatial understanding and procedural control [1-4]. Patient-specific 3D models are particularly valuable because they convert conventional two-dimensional image slices into an intuitive representation of individual anatomy, allowing the surgeon to examine the lesion, surrounding structures and candidate access corridors before intervention. Recent studies have shown that digital or printed patient-specific models can improve aspects of neurosurgical planning and training [1,5,6]. Computed tomography (CT) provides high-resolution volumetric information and is especially effective for defining the skull, calcified structures and surgical corridors. Contrast-enhanced CT can

additionally support visualisation of selected vascular and lesion-related structures. CT images can therefore provide the geometric basis for reconstructing a patient-specific 3D head and brain model. Nevertheless, CT has lower soft-tissue contrast than magnetic resonance imaging (MRI) for many intracranial structures.

For applications requiring detailed delineation of tumours, white matter or functional anatomy, the proposed CT-centred framework can be strengthened by multimodal registration with MRI or other clinical imaging [5,7]. The central concept is not that CT directly measures brain elasticity, but that CT supplies patient-specific anatomy and radiodensity information that can be combined with biomechanical measurements and inverse modelling to estimate mechanical properties. A major limitation of conventional neuronavigation is that preoperative images represent a largely static anatomy. Brain tissue is, however, highly deformable and exhibits nonlinear and time-dependent mechanical behaviour. Following craniotomy, cerebrospinal-fluid loss, gravity, retraction, tumour removal and direct instrument contact can cause substantial brain shift. As the anatomy deforms, the correspondence between the preoperative image and the actual sur-

gical field decreases. Finite-element and other biomechanical models have therefore been investigated as a means of predicting brain deformation and updating target location during surgery. Viscoelastic finite-element models evaluated against intraoperative benchmark data have demonstrated the capacity to reduce registration error and to represent clinically relevant inward brain shift [2]. Reliable prediction requires realistic mechanical properties. Brain tissue is heterogeneous, nearly incompressible, viscoelastic and sensitive to loading rate, physiological state and temperature.

Recent in-vivo work has demonstrated that human brain material parameters can be estimated by combining measured deformation with biomechanical modelling, supporting inverse identification as a feasible route to patient-specific tissue characterisation [8]. Where thermal instruments are involved, temperature also becomes important because thermal exposure can alter tissue mechanics and can produce irreversible damage. Recent thermomechanical characterisation and bioheat modelling studies reinforce the need to couple mechanical deformation with temperature and thermal-damage prediction for energy-based neurosurgical procedures [6,9]. Robotic and computer-assisted systems add a further challenge: the surgeon may be physically separated from the tissue and lose part of the natural tactile information used to judge contact, stiffness and force. Haptic technologies can restore kinaesthetic or tactile information to the operator. A 2023 meta-analysis across robot-assisted surgical studies reported that haptic feedback was associated with lower applied forces and improved task accuracy, although the magnitude of benefit depended on the task and feedback implementation [10].

Recent systematic and neurosurgery-focused reviews similarly identify haptic feedback as a promising component of surgical teleoperation and simulation, while emphasising current limitations in sensing, realism, latency and integration [11,12]. Accordingly, this project proposes an integrated framework with three linked aims. Aim 1 establishes patient-specific brain property identification using CT-derived anatomy together with inverse biomechanical estimation. Aim 2 develops a computational model of brain thermomechanical response, deformation, stress and tissue-damage risk. Aim 3 translates these predictions into surgical planning, visualisation and haptic-guided operation. The overall objective is to transform static patient imaging into a dynamic, mechanics-informed representation that can support target localisation, risk assessment and safer manipulation during brain surgery.

Theory

The proposed framework is founded on the integration of image-based anatomical reconstruction, inverse mechanics, nonlinear continuum modelling, bioheat transfer and model-based haptic rendering. The three aims are theoretically connected by the principle that patient-specific anatomy defines the computational domain,

experimentally informed mechanical properties define the tissue response, and the predicted response is then converted into visual and force information for surgical guidance.

CT-Based Patient-Specific Representation and Property Identification

CT attenuation is expressed in Hounsfield units (HU), which normalise the measured linear attenuation coefficient relative to water. In simplified form, $HU = 1000(\mu_t - \mu_w)/\mu_w$, where μ_t and μ_w are the attenuation coefficients of tissue and water, respectively. HU values are useful for image segmentation, anatomical classification and construction of the patient-specific geometry, but they should not be treated as a direct measurement of Young's modulus or viscosity. Instead, CT-derived anatomy and radiodensity are used as spatial priors, while mechanical properties are identified from the relationship between applied loading and measured deformation. Let θ denote the unknown material-parameter vector, for example $\theta = [E, \nu, \eta, \tau, \dots]$, containing elastic and viscoelastic quantities. For measured deformation y_m and model prediction $y_p(\theta)$, the residual is $r(\theta) = y_m - y_p(\theta)$. Assuming approximately Gaussian measurement/model errors with covariance R , maximum-likelihood estimation is equivalent to minimising the weighted residual energy:

$$\theta^* = \arg \min_{\theta} \frac{1}{2} r(\theta)^T R^{-1} r(\theta)$$

This formulation allows the mechanical parameters to be updated until the computed deformation best reproduces the measured physical response. It is consistent with contemporary inverse approaches for estimating in-vivo human brain properties [8].

Brain Deformation and Thermomechanical Response

At the continuum level, brain deformation is governed by conservation of linear momentum. For displacement u , density ρ , Cauchy stress σ and body force b , the dynamic equilibrium equation may be written as:

$$\rho \ddot{u} = \nabla \cdot \sigma + b.$$

Because brain tissue undergoes large deformation and exhibits time-dependent relaxation, σ is described by a nonlinear viscoelastic constitutive law. A hyperelastic component represents instantaneous nonlinear elasticity, while a relaxation component accounts for rate dependence and memory. Near-incompressibility is enforced through an appropriate volumetric constraint. Surgical-tool contact, gravity, retraction and cerebrospinal-fluid-related boundary changes enter the model as external loads and boundary conditions. The finite-element solution provides the evolving displacement field, stress, strain and brain-shift prediction. Prior work using viscoelastic finite-element models supports the relevance of these factors to image-guided neurosurgery [2].

For heat-generating procedures, the mechanical model is coupled to transient bioheat transfer. A commonly used representation is the Pennes equation:

$$\rho c \partial T / \partial t = \nabla \cdot (k \nabla T) + Q_s - \omega_b c_b (T - T_b)$$

where c is specific heat, k is thermal conductivity, Q_s is the surgical heat source, and the final term represents perfusion-mediated heat exchange. Temperature can influence material parameters and thus feed back into the deformation model. Irreversible thermal injury can be represented by an Arrhenius damage integral, $\Omega(t) = \int A \exp[-E_a/(RT)] dt$, where A and E_a are tissue-dependent kinetic constants. Bioheat and thermal-damage models have been used in neurosurgical laser applications, while recent measurements show that brain mechanical behaviour is temperature dependent [6,9].

Haptic Rendering and Safety-Guided Operation

The interaction force predicted at the virtual or robotic instrument tip provides the physical basis for haptic feedback. A simple local rendering relationship can be expressed as $F_h = -K_h \Delta x - C_h \Delta v$, where Δx and Δv are penetration/displacement and relative velocity, and K_h and C_h are effective stiffness and damping terms derived from, or calibrated against, the patient-specific tissue model. In the proposed system, these local forces are supplemented by model-predicted deformation, stress and thermal-damage indicators. When the instrument approaches a critical structure or when predicted loading approaches a safety threshold, the rendered force or virtual constraint can be increased to signal risk while preserving surgeon con-

trol. The theoretical objective is therefore not autonomous surgical decision-making, but a closed information loop in which patient-specific model predictions are translated into real-time visual and haptic cues [10,11,12].

Expected Results

The proposed theory is expected to produce a patient-specific computational representation in which CT-derived anatomy is linked to mechanically identified tissue properties rather than generic material constants alone (Figure 1). Aim 1 should yield a 3D anatomical model together with estimated elastic and viscoelastic parameters that reproduce observed tissue deformation within defined uncertainty. This should provide a more defensible basis for patient-specific simulation than directly assigning mechanical properties from CT intensity. Aim 2 is expected to generate spatial and temporal predictions of brain displacement, stress, strain and brain shift during surgical manipulation. For procedures involving a thermal source, the model should additionally provide temperature fields and tissue-damage indices. These predictions can be used to update the apparent location of the lesion and surrounding structures as deformation evolves. Aim 3 is expected to convert the predicted interaction forces and risk measures into an integrated visual and haptic interface, enabling the surgeon to compare candidate trajectories, recognise excessive loading and receive tactile cues during instrument-tissue contact. The principal quantitative outcomes would include tissue-property estimation error, target-registration error, deformation-prediction error, force-prediction error, peak interaction force and trajectory deviation.

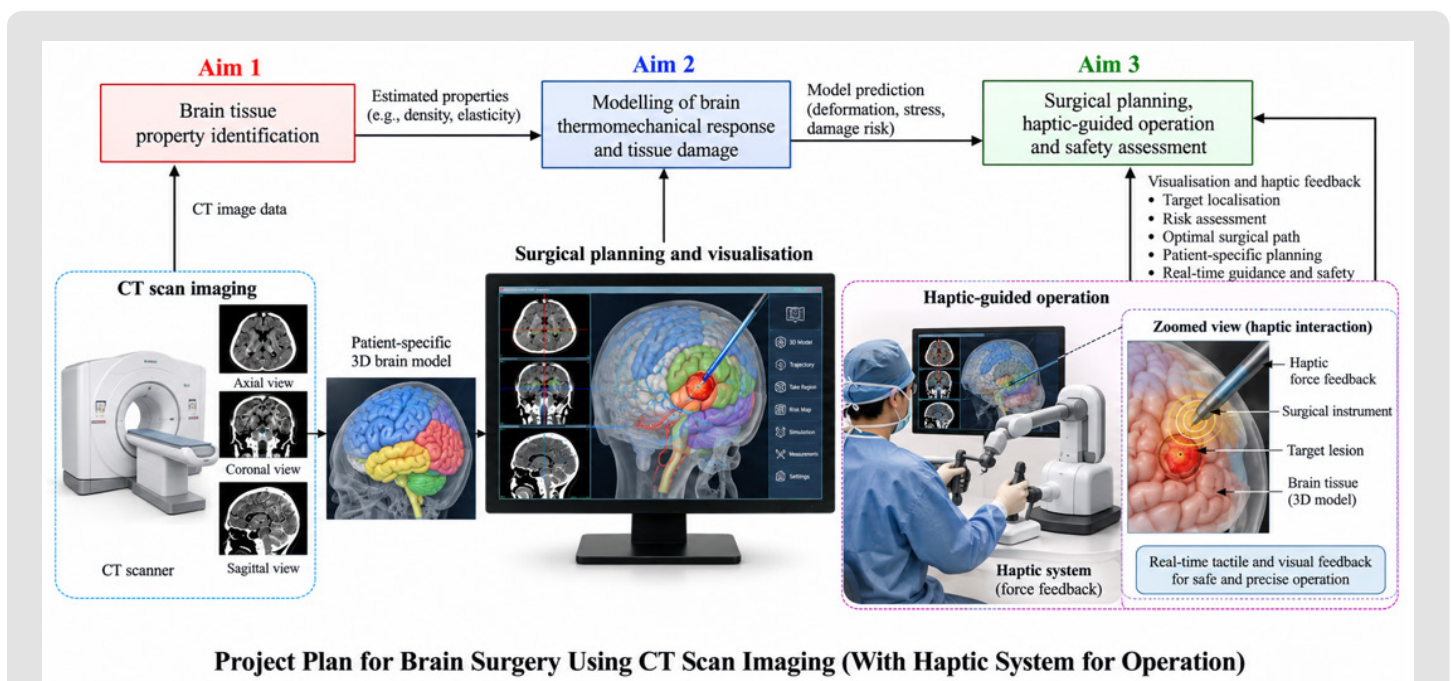


Figure 1: Project plan for CT image-based brain surgery with patient-specific modelling and haptic-guided operation.

Discussion

The main scientific contribution of the proposed framework is the transformation of CT-based anatomical imaging into a dynamic patient-specific model of surgical tissue response. Conventional image guidance provides an accurate preoperative reference but cannot, by itself, represent the mechanical evolution of the brain after the skull is opened and the tissue is manipulated. Brain shift therefore creates a fundamental mismatch between static image coordinates and the intraoperative surgical field. The proposed theory addresses this limitation by embedding patient anatomy within a nonlinear viscoelastic model whose parameters can be updated from measured deformation. This is consistent with evidence that finite-element models can improve prediction of intraoperative brain shift and that in-vivo brain properties can be estimated through inverse modelling [2,8]. A key revision in the proposed theory is the treatment of CT information. Although radiodensity can support segmentation and tissue classification, the relationship between CT attenuation and soft-tissue mechanical properties is not sufficiently direct to justify estimating elasticity from HU alone. The revised framework therefore separates anatomical information from mechanical identification: CT provides geometry and spatial priors, whereas deformation and force measurements provide the information required to identify elasticity, viscosity and related constitutive parameters.

This distinction improves scientific rigour and allows the system to incorporate additional measurements, including intraoperative imaging or instrument force data, when available. The thermomechanical component expands the framework beyond purely geometric brain-shift correction. This is particularly relevant when surgical instruments generate heat, such as laser or electrosurgical devices. Bio-heat transfer determines the spatial and temporal temperature field, while temperature-dependent mechanics determine whether local heating changes the deformation response. An Arrhenius-type damage integral provides a theoretical link between temperature-time history and irreversible injury. Recent neurosurgical modelling has shown the value of patient- and device-specific bioheat analysis for laser interstitial thermal therapy, and recent thermomechanical measurements demonstrate that brain viscoelasticity changes with temperature [6,9]. The thermal component should therefore be activated only when the surgical procedure contains a meaningful heat source; for purely mechanical procedures, the framework can operate as a deformation and stress model without unnecessary thermal complexity.

The haptic component translates model predictions into an additional sensory channel. Evidence from robot-assisted surgery indicates that haptic feedback can reduce average and peak interaction forces and can improve accuracy, although performance depends strongly on feedback type, task and operator experience [10]. A recent systematic review further notes that tactile feedback remains difficult to integrate because sensing and display technologies must be sensitive, compact, safe, responsive and compatible with the surgical workflow [11]. For neurosurgery specifically, simulation studies

and reviews indicate that haptic feedback can improve realism, but a fully integrated system capable of reproducing the complete procedure remains an open challenge [12]. These findings support the proposed use of haptics as an augmentation of visual guidance rather than as a substitute for the surgeon's judgement. Patient-specific 3D visualisation also has an important role in translating the model into clinically interpretable information. Studies published between 2021 and 2026 have reported benefits of patient-specific 3D models for surgical planning, education and simulation [1,5,6,13].

The proposed framework extends these approaches by attaching mechanical state variables to the anatomical model. Instead of displaying only the lesion and surrounding anatomy, the interface can also display predicted deformation, stress concentration, thermal exposure and safety margins. This creates a direct link between underlying biomechanics and surgical planning. Several challenges must be addressed before clinical translation. First, CT alone may be insufficient for detailed soft-tissue delineation, making CT-MRI registration advantageous for many intracranial applications [7]. Second, inverse identification is sensitive to measurement quality and parameter identifiability; multiple parameter sets can sometimes produce similar deformation responses, requiring regularisation and uncertainty analysis. Third, nonlinear 3D finite-element and thermomechanical models are computationally demanding, whereas haptic rendering requires very low latency. Reduced-order modelling, local model refinement and GPU acceleration will therefore be important for real-time implementation. Finally, haptic safety constraints must be designed so that feedback remains stable, intuitive and subordinate to surgeon control. The near-term role of the proposed platform is therefore best viewed as patient-specific decision support, planning and simulation, with progressive validation in phantoms and clinically representative datasets before any routine intraoperative deployment [14].

Conclusion

This revised project establishes a theoretical framework for CT image-based patient-specific brain surgery by integrating anatomical reconstruction, inverse tissue-property identification, nonlinear brain mechanics, thermomechanical modelling and haptic feedback. The key conceptual change from a conventional methodology section is that the relationships governing the system are explicitly defined: CT provides the patient-specific computational domain; measured deformation constrains the mechanical parameters; continuum mechanics predicts deformation and stress; bioheat theory predicts temperature and thermal damage when relevant; and model-predicted interaction forces are rendered to the surgeon through a haptic interface. The three aims form a coherent progression from characterisation to prediction and surgical guidance. Aim 1 identifies the tissue properties required to represent the individual brain. Aim 2 predicts brain shift, deformation, stress and, for thermal procedures, temperature and damage. Aim 3 converts these predictions into patient-specific surgical planning, visualisation and haptic cues.

The anticipated outcome is a dynamic model that informs the surgeon not only where the lesion and critical structures are located, but also how the surrounding brain is expected to respond to manipulation. With rigorous validation and careful management of computational latency and uncertainty, this framework could support safer and more precise neurosurgical planning, simulation and future robot-assisted intervention.

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