Automatic Nonrigid Registration for Tracking Brain Shift during Neurosurgery

J. Rexilius[1,2] H. Handels[3], A. Nabavi[2,4], R. Kikinis[2], and S.K. Warfield[2]

[1] MeVis, Center for Medical Diagnostic Systems and Vsualization, Bremen, Germany
[2] Surgical Planning Laboratory, Harvard Medical School & Brigham and Women's Hospital, Boston, MA, USA
[3] Institute for Medical Informatics, Medical University of Luebeck, Germany
[4] Department of Neurosurgery, Kiel University, Germany
email: rexilius@mevis.de

Abstract. Intraoperative imaging is used more frequently today since this enables the surgeon to localize structures inside the brain more accurately and helps to detect shape changes. In order to combine informations derived at different time points, we describe a nonrigid registration algorithm that aligns MR scans of the brain.

Based on a set of feature points, an initial sparse estimate of the displacement field is found by optimizing a local cost function. A linear elastic model is then used to infer the volumetric deformation across the image. Inhomogeneous elasticity parameters are generated using empirically observed variability of the brain from a dataset of 154 young adults. Initial results are generated on intraoperative image sequences showing brain shift.

1 Motivation

Shape changes of the brain (*brain shift*) during neurosurgery caused by the intervention and physiological changes are today commonly considered as nonrigid deformation. Since the time constraints for preoperative imaging are usually less crucial, more image information for example due to segmentations can be obtained before surgery. In order to use this information during surgery, an important issue is to develop robust and accurate nonrigid registration algorithms that align the pre- and intraoperative data. Since it is often not feasible to measure directly the deformation occurring at each voxel, the deformation field is first estimated at sparse locations which have to be interpolated throughout the image.

Works concerning registration based on physical models of the underlying deformable objects have become popular [1,2], since they have the potential to constrain the underlying deformation in a plausible manner.

A large amount of work has been done in the field of image guided surgery. A sophisticated biomechanical model was proposed in [3] with the drawback of its limitation to 2D images and a required manual interaction. Another finite element approach was proposed in [4]. Warfield et al. [5] described a fast parallel implementation using an approach for image guided neurosurgery that was applied during surgery. They proposed a biomechanical model similar to that in [2], constrained at the boundaries of the brain and ventricles.

In our work we propose a linear elastic model based on continuum mechanics constrained everywhere the image provides sufficient information to estimate the true displacement, rather than to restrict the method to certain areas of the brain. For computational efficiency, a parallel implementation was developed for each part of the algorithm. Furthermore, we introduce a new model for inhomogeneous elasticities based on an entropy measure.

2 Method

We formulate the registration process as an energy minimization problem between a reference and a template image.

In order to obtain suitable feature points that can be used to automatically generate a correspondence between the two images, we calculate the gradient magnitude out of blurred image intensities, using a nonlinear diffusion filter [6] at first. The associated partial differential equation is solved by an additive operator splitting (AOS) scheme. Only voxels higher than two standard deviations above the mean of the magnitude of the gradient are then used for the following correspondence detection.

The correspondence between reference and template image for the extracted feature points is computed by a template matching approach. Our work uses the local normalized cross-correlation, which is maximized with an exhaustive search strategy.

The sparse deformation estimates computed before are now introduced as external forces into a linear elastic model. The underlying idea is to restrict the registration process so that the resulting deformation field is a priori fixed by the estimates at these points. Changes in the object's shape result in an equilibrium state of energy with a displacement u that minimizes the total potential energy given as

$$E(u) = \frac{1}{2}\int_{\Omega} \sigma^{\top} \varepsilon \, d\Omega \; - \; \int_{\Omega} u^{\top} F \, d\Omega \,,$$

where the first term describes the work provided by the stress σ along the strain $\varepsilon = Lu$ and the second term the external work. The relationship between stress and strains is described by Hooke's law as $\sigma = C\varepsilon$ with elasticity matrix C. The associated equation is solved by a finite element approach [7] using linear shape functions and a regular mesh of tetrahedra. For a typical volume size (256x256x124), the total execution time for 12 750MHz UltraSPARC-III CPUs is about 5 1/2 minutes.

2.1 Inferring empirically observed anatomical variability

As our approach is limited to isotropic material, two parameters are needed for the elasticity matrix C to describe the mechanical behavior of tissue undergoing a deformation: Young's modulus E as a measure of stiffness and Poisson's ratio ν as a measure of incompressibility. Typically, elasticity parameters have been set arbitrarily and homogeneously [1,2] which is only a rough approximation of the underlying tissue.

We present here a new scheme in that inhomogeneous elasticity parameters are derived from an empirical estimate of anatomical variability, so that each discrete element can obtain its own material properties during the matrix assembly of the linear elastic model. The entropy of the segmented tissue classes [8] (white matter, gray matter, CSF, and background) present at each voxel [9] is

$$h(s) = -\sum_{i=1}^{4} p(s_i)\log(p(s_i))$$

with the probabilities $p(s_i)$ determined from alignment of the tissue classifications of 154 subjects using a global affine transformation [10] and our nonrigid method. Since regions with low entropy represent regions with empirically determined low anatomical variability and regions with high entropy represent regions with empirically determined high anatomical variability, a linear mapping is used to assign elasticity parameters based upon the entropy of each voxel, i.e. low entropy values are assigned to low elasticity parameters. Furthermore, the background is set to a low elasticity value.

This model of anatomical variability is most suited for inter-subject registration. Here we apply this model in the context of intra-subject registration. We intend to construct a model for intra-subject brain shift from MRI observations of the variation of brain shift in these surgeries using the method describes above, as soon as a sufficiently large number of observations have been made.

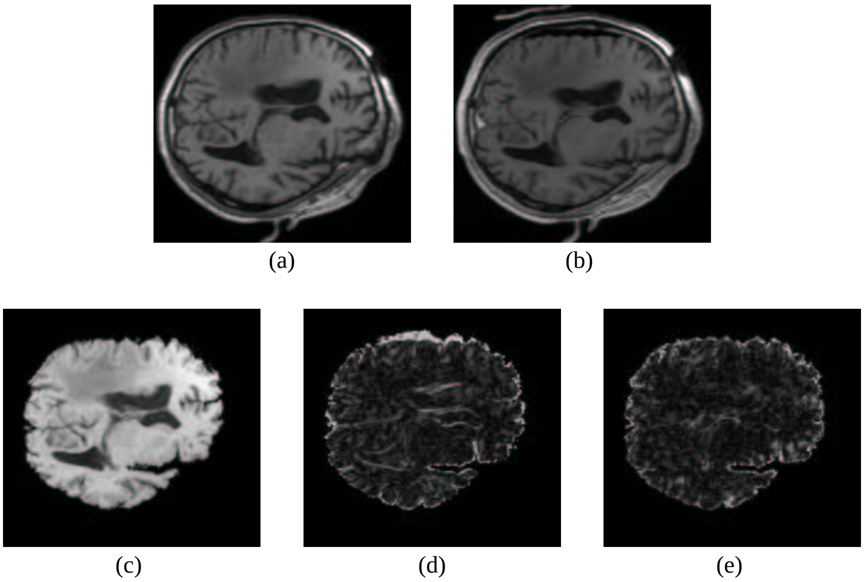
3 Experimental results

We applied our method to three neurosurgical cases showing brain shift. Since a linear elastic model cannot cope with the massive change of a patients anatomy during craniotomy, when part of the skull is opened and removed and the skin flap is folded back, the algorithm was applied only to the brain and not the whole MR scan. Figure 1 displays a slice of an MR scan before and after craniotomy, the deformed brain, and the difference image before and after registration. It can be observed that the brain shift was successfully captured. The norm of the difference image decreased by about 20% in all cases. More validation experiments with appropriate landmarks defined by physicians are required to accurately assess the potential of this method.

4 Discussion and Conclusion

The physics-based linear elastic model provides us with the ability to simulate realistic deformations. Furthermore, timing experiments show that our algorithm could be suitable for the real-time constraints of neurosurgery.

Future work will investigate alternative similarity measures and feature extractions. We also plan to enhance this approach incorporating the anisotropy of certain brain tissue structures.



(a) (b)

(c) (d) (e)

Fig. 1. Elastic matching applied to MR scan of the brain obtained during neurosurgery. (a) Slice from an early stage of the surgery; (b) Slice after craniotomy; (c) Deformed image; (d) Difference image before alignment; (e) Difference image after alignment.

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