INTEGRATING STRUCTURAL AND DIFFUSION MR INFORMATION FOR OPTIC RADIATION LOCALISATION IN FOCAL EPILEPSY PATIENTS

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ABSTRACT

Current state of the art neurosurgical systems do not exploit the complementary information provided by structural and diffusion MRI when aligning pre-operative and intra-operative images. We propose a multivariate registration scheme where structural and fractional anisotropy data are combined in a single similarity measure. We formulate the normalised mutual information expression for the multichannel scheme and compute its analytical derivative. The method was validated using both a numerical phantom and clinical data using pre and post-operative images from patients who had undergone surgery for treatment of refractory focal epilepsy and shows correlation between visual field deficit and predicted damage to the optic radiation. This work could be of significant utility in image-guided interventions and facilitate effective surgical treatments.

Index Terms— multivariate registration, optic radiation localisation, interventional MR

1. INTRODUCTION

Around one-third of patients with focal epilepsy are refractory to treatment with anti-epileptic drugs. Anterior temporal lobe resection is an effective treatment for such patients with refractory temporal lobe epilepsy [1]. However, a careful balance has to be established between obtaining seizure control and minimising the chance of causing new morbidity. Significant morbidity can result from damage to eloquent grey matter regions of the brain or critical white matter tracts. One major source of morbidity in these cases is the damage to the optic radiation during the intervention. Hence, accurate localisation of optic radiation is critical in improving the surgical outcome for patients undergoing anterior temporal lobe resection.

Current neurosurgical protocols require acquisition of images using multiple modalities, for example, T1-weighted, T2-weighted and diffusion tensor (DT) magnetic resonance (MR) images. These images can often provide unique and complementary information about the underlying tissue. Structural MR images can capture information at the interfaces between the different brain tissues while DT-MR images can provide information about organizational structure of the white matter fibre bundles. The fusion and presentation of information to the surgeons from these images could facilitate critical surgical decisions and improve the ultimate surgical outcome. The current commercial image-guided neurosurgical systems do not perform non-rigid mapping between the pre and intra-operative images due to the inherent time constraints in a neurosurgical procedure. They also do not exploit the shared information between these complementary images. This limitation reduces their accuracy in providing accurate localisation of objects of interest. Archip et al [2] demonstrated a neurosurgery system that performs non-rigid registration and can visualise data from various imaging modalities. However, they do not exploit the shared information between these images in their registration scheme.

Park et al [3] used a multiple-channel demons algorithm to normalise DT-MRI data and applied it to creation of group diffusion tensor atlas. They performed registration using different combination of channels to simultaneously map structural and diffusion images. Similarly, Avants et al [4] presented a multivariate approach...
that uses fused structural and diffusion tensor data. This method also performs simultaneous registration without exploiting the shared information between the different images. More recently, Studholme [5] introduced a modified mutual information (MI) derived criterion called diffusion paired MI which combines structural information and diffusion tensor data in a unified measure. He formulated the similarity measure based on the assumption that the different diffusion weighted channels are relatively uncorrelated and a single measure can be formed by summation of the mutual information between the structural image and each of the diffusion channels. This method uses the full tensor component and needs the computation of multiple 4-dimensional joint histograms and is not suitable to be used within the surgical setting.

In this paper, we present a multivariate registration framework based on a multichannel normalised mutual information (NMI) similarity measure with the view to eventually applying it in real time surgical settings. The proposed method makes use of the shared information between structural MR images and fractional anisotropy (FA) from DT-MRI. We formulate the expression for the analytical derivative of the proposed similarity measure and validate our algorithm using both numerical phantom and clinical data from patients who had undergone surgery for refractory focal epilepsy treatment.

2. METHODS

We propose a multivariate normalised mutual information measure to estimate a transformation $\mathbf{T}$ between two pairs of images $\{R_1, R_2\}$ and $\{F_1, F_2\}$. The transformation is parametrised using a cubic B-Spline model, as in Rueckert et al. [6] where each degree of freedom is noted as $\mu_{i,j,k}^{\beta}$ with $i, j, k$ being the index of the parameter and $\xi$ denoting the three components, one along each axis. Both reference images $R_1$ and $R_2$ are aligned with each other using rigid registration. Similarly, the floating images $F_1$ and $F_2$ are also rigidly aligned. The warped images using $\mathbf{T}$ are noted as $F_1(\mathbf{T})$ and $F_2(\mathbf{T})$.

The NMI in the proposed framework is computed as follows:

$$\text{NMI}(R_1, R_2, F_1(\mathbf{T}), F_2(\mathbf{T})) = \frac{H(R_1, R_2) + H(F_1(\mathbf{T}), F_2(\mathbf{T}))}{H(R_1, R_2, F_1(\mathbf{T}), F_2(\mathbf{T}))},$$

where $H(R_1, R_2)$ and $H(F_1(\mathbf{T}), F_2(\mathbf{T}))$ represent the joint entropy between the two reference images and the two deformed floating images respectively. $H(R_1, R_2, F_1(\mathbf{T}), F_2(\mathbf{T}))$ is the joint entropy between the four input images and is computed using Shannon’s formula for entropy as:

$$H(R_1, R_2, F_1(\mathbf{T}), F_2(\mathbf{T})) = -\frac{1}{N} \sum_{r_1, r_2, f_1, f_2} p(r_1, r_2, f_1, f_2) \times \log(p(r_1, r_2, f_1, f_2)),$$

where $r_1$, $r_2$, $f_1$ and $f_2$ are the voxel intensity of images $R_1$, $R_2$, $F_1((\mathbf{T}))$ and $F_2((\mathbf{T}))$ respectively.

Each probability is computed using a joint histogram $H$ as:

$$p(r_1, r_2, f_1, f_2) = \frac{\mathcal{H}(r_1, r_2, f_1, f_2)}{\sum_{r_1, r_2, f_1, f_2} \mathcal{H}(r_1, r_2, f_1, f_2)},$$

where we used a Parzen Window [7] to fill the histogram:

$$\mathcal{H}(r_1, r_2, f_1, f_2) = \sum_{\vec{x} \in \mathbf{R}} [\beta^3(R_1(\vec{x}), r_1) \times \beta^3(R_2(\vec{x}), r_2) \times \beta^3(F_1(\mathbf{T}(\vec{x})), f_1) \times \beta^3(F_2(\mathbf{T}(\vec{x})), f_2)]$$

where $\beta^3$ is a cubic B-Spline kernel.

The similarity measure is optimised using a conjugate gradient descent scheme that requires computation of the first derivative of the similarity measure. In order to compute the derivative of the NMI, one must compute the derivative of each joint entropy. This can be achieved by computing the derivative of the probability of each group of intensities. The derivative of each probability can be calculated by computing the derivative of the joint histogram according to each degree of freedom such as:

$$\frac{\partial \mathcal{H}(r_1, r_2, f_1, f_2)}{\partial \mu_{i,j,k}^{\beta}} = \sum_{\vec{x} \in \mathbf{R}} \beta^3(R_1(\vec{x}), r_1) \times \beta^3(R_2(\vec{x}), r_2) \times \left( \frac{\partial \beta^3(u, f_1)}{\partial u} \left.\frac{\partial F_1(p)}{\partial p} \right|_{p=F_1(\mathbf{T}(\vec{x}))} \frac{\partial \mathbf{T}(\vec{x})}{\partial \mu_{i,j,k}^{\beta}} \times \beta^3(F_2(\mathbf{T}(\vec{x})), f_2) + \beta^3(F_1(\mathbf{T}(\vec{x})), f_1) \times \frac{\partial \beta^3(u, f_2)}{\partial u} \left.\frac{\partial F_2(p)}{\partial p} \right|_{p=F_2(\mathbf{T}(\vec{x}))} \frac{\partial \mathbf{T}(\vec{x})}{\partial \mu_{i,j,k}^{\beta}} \right).$$

In order to promote a smooth transformation, the objective function is composed of the multichannel NMI with the bending energy (BE) of the spline as the penalty term. Therefore, one must also compute the derivative of the BE in the optimisation scheme. We refer the reader to Modat et al. [8] for the computation of the BE analytical derivative.

3. VALIDATION

Numerical Phantom We constructed a numerical phantom to estimate the accuracy of the proposed registration framework. For the structural image phantom, see figure 1(a), a very high resolution digital phantom
Fig. 1. Figure (a) showing the simulated grey matter and figure (b) shows the simulated white matter tracts.

containing finger and sheet like collapsed sulci and gyri was created, simulating the structure of the cortex. The phantom was created on a 0.25 mm equivalent isotropic image with a size of 180 × 180 × 120 voxels. Gaussian noise was added in the Fourier domain to create the Rician noise corrupted phantom. The fibre tracks were created to span the white matter region of the phantom as shown in figure 1(b).

The validation was done by applying known deformations to the phantoms. Three different registration schemes were used. First, the structural phantom was registered to the deformed structural phantom to simulate registration between anatomical images. Secondly, the WM phantom was registered to the deformed WM phantom to simulate registration using the complementary diffusion imaging modality. Finally, we registered the images using our proposed registration framework using the multivariate NMI as the similarity measure. We performed the analysis by repeating the experiment with 100 different deformations. The results over the whole phantom and the white matter area are illustrated in table 1.

<table>
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<tr>
<th></th>
<th>Init.</th>
<th>Struct.</th>
<th>Tract</th>
<th>Joint</th>
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<tr>
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<td>1.16(0.03)</td>
<td>1.60(0.03)</td>
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<td>WM</td>
<td>1.70(0.09)</td>
<td>1.06(0.07)</td>
<td>0.94(0.08)</td>
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Table 1. Mean (std) Euclidean distance errors. The second column quantifies the initial misalignment. Subsequent columns correspond to the error after registration using the structural information, the tract information and the joint information respectively. Errors are computed within the whole phantom (All) (middle row) and the white matter (WM) (bottom row).

Subject Data We used data from 16 subjects that had undergone temporal lobe resection for treatment of refractory focal epilepsy. Significant visual field deficits (VFD) can be caused by damage to optic radiation during the intervention. We analysed the pre and post-operative MRI scans and correlated the visual field deficit, which was determined by a visual field assessment, with the optic radiation resection as predicted by the different registration schemes. Standard clinical sequences were performed on a 3T GE Excite II scanner (General Electric, Waukesha, Milwaukee, WI, USA) including a T1-weighted coronal volumetric acquisition with a spatial resolution of 0.9 × 0.9 × 1.1 mm. DTI data was acquired using a single-shot spin-echo planar imaging (EPI) sequence with a spatial resolution of 1.9 × 1.9 × 2.4 mm.

VFD Quantification Pre and postoperative visual fields were assessed by Goldmann perimetry using three isoptres (V/4e, V/2e, I/2e) but only the largest (V/4e) was used for analysis. The degree of postoperative visual field loss was quantified as:

\[
VFD = 1 - \frac{\text{area of upper quadrants contralateral to resection}}{\text{area of upper quadrants ipsilateral to resection}}
\]

Automatic skull-stripping [9] was performed on the images prior to registration to ensure that all non-brain related tissues were removed from the image. The optic radiation track was identified in the pre-operative diffusion images by conducting probabilistic tractography using Camino [10]. A multitensor model was used for the tractography and the resulting probability map was thresholded at 0.05.

We registered the pre-operative dataset to the post-operative dataset using only anatomical images, only diffusion images and using the proposed method. We propagated the optic radiation using the deformation field generated by the three registration schemes. The damage to the optic radiation was quantified by measuring the anteroposterior distance from the anterior part of Meyer’s loop to the front of the resection margin in a straight line (A-P) measured in mm. This is illustrated in figure 2. The validation results are shown in table 2. The proposed registration scheme correlates with the measured visual field deficit (Pearson correlation coeffi-
cient: 0.94, $p < 0.001$). There is a trend towards higher correlation for the proposed method. The anatomical registration failed to predict the VFD correctly for 2 subjects (case 6 and 9) while the diffusion only scheme failed for one subject (case 3). There were no such failures for the proposed scheme.

**Computation Time** Average computation time using a CPU implementation was 17.5 minutes with a standard deviation of 2.5 minutes. As shown in [8, 11] significant speed increase could be achieved through the use of graphical processing units (GPUs).

## 4. DISCUSSION AND CONCLUSION

We presented a registration framework that can exploit shared information between different images. We formulated the analytical derivative for the multichannel NMI and demonstrated the accuracy of the algorithm on both a numerical phantom and clinical data. The initial results using FA information are promising but needs further validation with more clinical data to do a more rigorous comparison with anatomical and diffusion only registration schemes and quantify the gain coming from the use of shared information. Future work will integrate the GPU version of the proposed NMI into the framework described in [11] to make it suitable for real time surgical guidance systems.

## 5. REFERENCES


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http://sourceforge.com/projects/niftyreg

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<table>
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<tr>
<th>Case</th>
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**Table 2.** Pearson Correlation coefficient (CC) of the measured visual deficit against the predicted damage to the optic radiation by using the three registration schemes. Columns 3-5 show the predicted damage to the optic radiation. Values of 0 or less indicates no damage (no overlap between the optic radiation and the resection). Values less than 0 were clipped to 0 for the purposes of CC calculation. The figures in italics indicate where the predicted damage does not correctly indicate the occurrence of visual deficit. The last two rows show the CC of the A-P distance against the visual field assessment scores for all subjects and subjects with VFD.