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Towards automated correction of brain shift using deep deformable magnetic resonance imaging-intraoperative ultrasound (MRI-iUS) registration

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Abstract: Intraoperative brain deformation, so-called brain shift, affects the applicability of preoperative magnetic resonance imaging (MRI) data to assist the procedures of intraoperative ultrasound (iUS) guidance during neurosurgery. This paper proposes a deep learning-based approach for fast and accurate deformable registration of preoperative MRI to iUS images to correct brain shift. Based on the architecture of 3D convolutional neural networks, the proposed deep MRI-iUS registration method has been successfully tested and evaluated on the retrospective evaluation of cerebral tumors (RESECT) dataset. This study showed that our proposed method outperforms other registration methods in previous studies with an average mean squared error (MSE) of 85. Moreover, this method can register three 3D MRI-US pair in less than a second, improving the expected outcomes of brain surgery.

Keywords: biomedical image processing; brain shift; deep learning; image-guided neurosurgery; MRI-iUS.

Introduction

Accurate localization of the pathologic targets such as tumors inside the brain is one of the most challenging tasks during neurosurgery [1] because it is difficult to distinguish between pathologic structures and the healthy tissue based only on visual inspection. In addition, the brain deforms its shape in response to surgical manipulation such as dura opening, gravity, loss of cerebrospinal fluid, and swelling due to osmotic drugs and anesthesia, which results in the so-called brain shift. This may lead to a change in the tumor's position and thus limits the utility of preoperative image data for intraoperative guidance in neurosurgery [2].

The use of preoperative magnetic resonance imaging (MRI) as the basis for intraoperative navigation is a well-established option for neurosurgical guidance during surgery [3]. Further, using intraoperative MRI can provide excellent visualization of the brain tissues including substructure and surrounding tissues [4]. However, intraoperative MRI is limited because of long scan times and the need for special precautions in the operating room to avoid the degradation of MRI scanning quality or artifacts. On the other hand, intraoperative ultrasound (iUS) offers portable, low cost with fast scan times ranging from seconds to minutes. The iUS modality is also easy to use and allows for a spatial resolution within 0.50 mm. But it is prone to a decrease of imaging quality during surgery mainly due to attenuation artifacts based on the different speed of sound in water and brain tissue. Therefore, registration of MRI scans taken in the planning phase with the iUS images during the surgical procedure has been suggested to correct the tissue shift of the brain.

Medical image registration is the process of aligning two or more sets of imaging data into a common coordinate system [5]. It plays a main role in comparing and combining imaging data acquired with different modalities from various viewpoints and at different times [6]. Primarily, classical image registration approaches have been proposed with two primary types: feature-based and intensity-based matching [7]. Besides, these approaches depend on one pair of images with prior domain knowledge and require robust parameter tuning and setting [7].

Recently, deep learning approaches are widely used in the field of artificial intelligence and computer vision, especially for medical applications such as anatomical and

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pathological feature extraction, and tumor segmentation [8]. By exploiting image pairs during the training stage, deep learning methods can optimize over all training sets providing a general solution that reflects all parts of the dataset. Moreover, these approaches can provide fast image registration assisting neurosurgeons to define the position and size of the brain shift in real-time.

Nevertheless, aligning preoperative MRI and iUS for brain shift correction is still a challenging problem due to the different characteristics of each modality and the type of information they provide. Consequently, only a few studies have applied deep learning on registering preoperative MRI and iUS for brain shift correction [9–11]. In this paper, a fast and robust deep learning-based method for automatic preoperative MRI and interventional US registration is presented to assist the neurosurgeons by correcting brain shift intraoperatively.

Methodology

The deformable image registration is considered as an optimization problem, in which a moving image (IM) is transformed into the space of the fixed image (IF). Let ϕ be the deformation field that relates the two images. Then, the energy function ε is calculated by the following equation:

$$\varepsilon = S(I_F, I_M \cdot \phi) + R(\phi) \tag{1}$$

where S denotes the similarity metric of the aligned image $(I_M.\phi)$ and the fixed image I_F, and R represents a regularization term corresponding to the bending energy. In this study, iUS data are used as the fixed image and MRI scans are used as moving images since we aim to reflect the brain shift in the iUS data.

Figure 1 depicts the workflow of our proposed deep registration method. Firstly, the moving image (preoperative MRI) and the fixed image (iUS) are provided to the convolutional neural network (CNN), which computes the transformation field ϕ. Then, the moving image is warped into $(I_M.\phi)$ using a linear re-sampler.

Similar to U-Net [12] architecture and our previous enhancement [8], the CNN consists of two paths: a feature extractor and an image upscaling. The first part is a contracting path that consists of repeated $3 \times 3 \times 3$ convolutions followed by an activation unit and a $2 \times 2 \times 2$ max pooling for down-sampling. By using a stride of 2, the spatial dimension in each step is reduced to the half, like traditional pyramid registration architectures. In the image upscaling path, each step consists of a consecutive up-sampling layer, $2 \times 2 \times 2$ up-convolution, a batch normalization layer, and a rectified linear unit (ReLU). Then, the learned features from the first path are propagated through a skip connection that recombines it with higher resolution outputs from the second path, respectively.

Due to the applied two-step registration approach, the loss function consists of two components: $\mathcal{L}_{sim}$ quantifies the image similarity between the warped image $(I_M.\phi)$ and the ground truth warped image I_W. $\mathcal{L}_{disp}$ presents the differences between ground truth and predicted deformation fields, such that $\mathcal{L}_{sim}$ and $\mathcal{L}_{disp}$ are estimated using the mean squared error (MSE) and difference in spatial gradients of displacements d and d_{Truth} as follows:

$$\mathcal{L}_{sim} = MSE = \frac{1}{|X|} \sum_{p \varepsilon X} \left((I_W(p) - \phi.I_M(p)) \right)^2 \tag{2}$$

$$\mathcal{L}_{disp} = \sum_{p \varepsilon X} \| d_{Truth}(p) - d(p) \| \tag{3}$$

Experiments

Data and experimental setup

This study was performed using the public REtroSpective Evaluation of Cerebral Tumors (RESECT) dataset [13]. The dataset includes pre-operative MRI, iUS images, and expert-labeled anatomical landmarks from 23 patients who have received surgeries of low-grade gliomas (Grade II) at St. Olavs University Hospital, USA. MRI scans include two

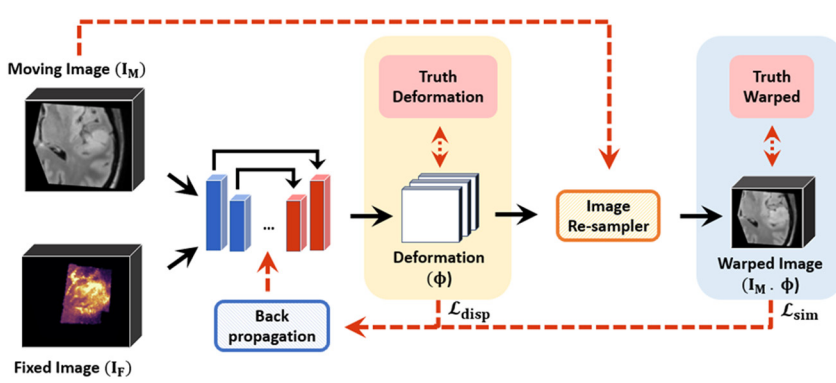

Figure 1: The workflow of the proposed deformable magnetic resonance imaging-intraoperative ultrasound (MRI-iUS) registration method using a 3D convolutional neural network. Dashed red arrows indicate process steps performed only in the training stage.

modalities: T1-weighted Gd-enhanced and T2-weighted fluid-attenuated inversion recovery (FLAIR) with a voxel size of $1 \times 1 \times 1$ mm^3, whereas interventional 3D US data cover the entire tumor region at three different surgical stages: before opening the dura, during and after tumor resection with resolutions ranging from $0.14 \times 0.14 \times 0.14$ mm^3 to $0.24 \times 0.24 \times 0.24$ mm^3.

In our experiments, MRI T2-FLAIR and iUS before opening the dura images are utilized as the moving I_M and fixed I_F images, respectively. Since MRI and iUS scans are acquired using two different settings, a pre-processing stage is mandatory. First, the iUS images are resampled to the same voxel resolution of the moving images of $1 \times 1 \times 1$ mm^3. After that, T2-FLAIR images are cropped to the same orientation and dimension in the iUS scanning. Then, all images are downsampled to a resolution of $128 \times 128 \times 96$ for efficient CPU and memory consumption. The training phase contains 18 pairs of MRI and iUS images, whereas the remaining four cases are used for the testing phase. The proposed method was implemented in Python using Keras library and Tensor Flow backend. Adam optimizer starting at a learning rate of 0.0001 and a batch size of four was used.

Results and evaluation

The performance of our proposed method has been evaluated and compared with three public well-known registration methods. The first method is the symmetric image normalization method (SyN) as part of the Advanced Normalization Tools (ANTs) [14], where the similarity measure is cross-correlation (CC). The second method is asymmetric block-matching registration as part of the NiftyReg open source package [15]. The dense displacement sampling registration (deeds) [16] is utilized as the third baseline method.

Figure 2 shows the results of aligning two MRI T2-FLAIR (moving images) to intraoperative US (fixed images) using our proposed method. The columns show the preoperative MRI, the intraoperative US, the overlap of both images before and after deformable registration using the proposed method. In the upper case (Patient 14), our proposed method is able to align correctly the brain tumor (*blue arrows*) as well as sulci (*white arrows*). On the other hand, our trained network attempted in the second case (Patient 8) to penalize the MSE of the tumor boundaries, but other structures are affected and have a larger registration error than initial registration. Nevertheless, this gives better MRI-US registration results than the initial alignment.

For further evaluation of the proposed model, two different metrics are compared against state-of-the-art image registration techniques and summarized in Table 1: First, the MSE (refer to Eq. (2)) between predicted deformed MRI and ground truth, generated using the MINC toolkit (https://bic-mni.github.io/), is calculated. Second, the average runtime of the three experimented methods as well as our proposed approach are listed in the last row. As shown in the results, the proposed registration method

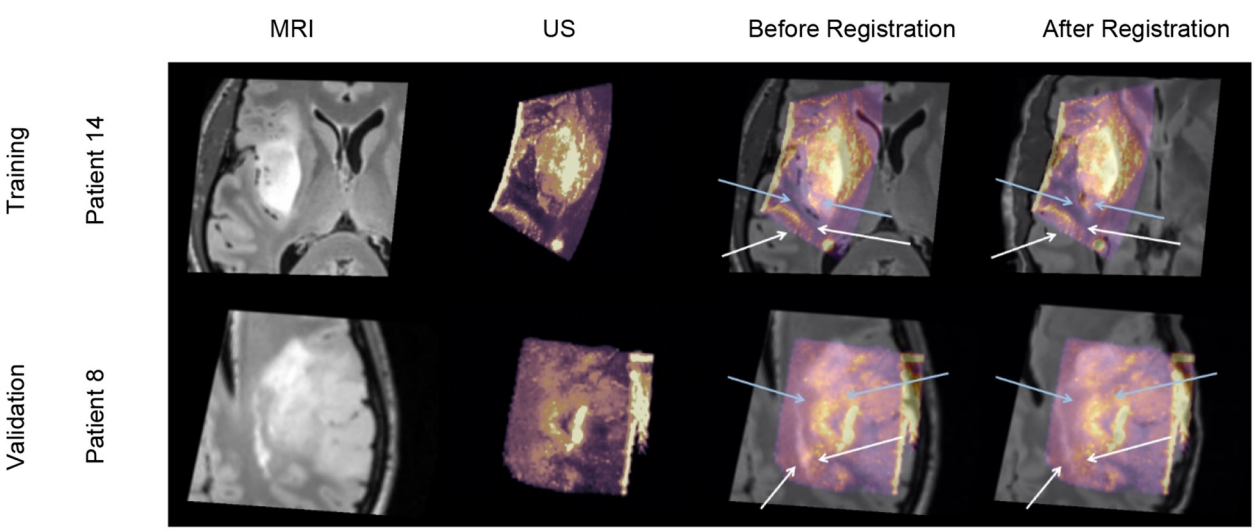

Figure 2: A sample of MRI-iUS registration results using the proposed deep registration method. The original MRI (moving image) and colored iUS (fixed image) are shown in the first two columns. The overlay results of iUS images on MRI before and after registration procedure are presented in the third and fourth columns, respectively. The arrows indicate brain shift for tumor (*blue*) and other anatomical structures such as sulci (*white*).

Table 1: Evaluation results of the proposed approach compared with classical methods on the retrospective evaluation of cerebral tumors (RESECT) dataset. For each case, mean squared error (MSE) calculations are listed. The last row represents the average runtime (in seconds). Four validated cases are indicated in bold.

Pair #	Initial	ANTs	NiftyReg	Deeds	Ours
Patient 1	1678	960	1505	825	109
Patient 2	1097	604	937	515	40
Patient 3	633	406	588	334	43
Patient 4	852	462	745	382	90
Patient 5	993	670	884	823	74
Patient 6	846	414	836	427	32
Patient 7	1248	626	1108	758	28
Patient 8	1117	641	865	588	132
Patient 9	1152	445	938	746	59
Patient 10	2053	1023	1793	1286	58
Patient 11	2618	2105	2193	1912	23
Patient 12	3545	1725	2832	883	61
Patient 13	1057	790	919	820	12
Patient 14	1829	1303	1532	1244	67
Patient 15	836	634	718	587	27
Patient 16	1748	517	1407	1117	26
Patient 17	4073	1429	2879	1477	71
Patient 18	2614	975	1844	903	38
Patient 19	1532	567	1178	560	13
Patient 20	3958	2372	3135	2109	717
Patient 21	3802	2647	3242	2273	46
Patient 22	4248	2186	3309	1990	107
Avg. MSE	1979	1068	1608	1025	85
Avg. time		1862.0	14.5	55.0	0.317

outperforms the other methods in terms of MSE and average runtime. With an average MSE of 85, the proposed method is significantly better than classical approaches that yield average MSE of 1068, 1608, and 1025 for ANTs, NiftyReg, and deeds, correspondingly. Remarkably, more than three 3D MRI-US registrations per second can be performed on the same GPU using our proposed method. On the other hand, classical approaches fail to provide a similar performance ranging from an average of 14.5 s for NiftyReg to 1862 s (31 min) for ANTs software.

Conclusion

In this study, a 3D deep convolutional neural network-based deformable MRI-iUS image registration was proposed. The proposed registration method can successfully correct brain shift (see Figure 2). Moreover, our deep registration method is fully automated and outperforms the state-of-the-art image registration methods in terms of both mean squared error and average runtime, as illustrated in Table 1.

We are currently working on improving and validating the proposed deep MRI-iUS registration in the clinical routine of neurosurgery to enhance brain shift correction. The overall registration performance will be further analysed using other metrics such as target registration errors (TREs).

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