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Estimating the registration error of MRI brain data based on regression U-Net

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Abstract

Magnetic resonance image (MRI) distortions and registration of MRI on computed tomography (CT) are the main sources of error in the setting of brain stereotactic surgeries. The outcome of several key brain surgeries, such as deep brain stimulation (DBS), are today directly dependent on stereotactic precision. However, the registration error estimation (REE) is a challenging task due to the lack of ground-truth. To address this problem, we propose a U-Net regression model that is able to estimate registration errors. Our experiments on MRI mono-modal registration provided preliminary results that are comparable to those in previous similar works.

Keywords

Registration error, image registration, brain MRI, convolutional neural networks, U-Net.

1 Introduction

Brain surgery requires considerable precision in many procedures, both for identifying anatomical regions and for instrument insertion. An example is the Deep Brain Stimulation (DBS), which is an electrode implantation with the goal of stimulating precise neural fibers inside the brain. Especially, it is widely used to alleviate dyskinesia of patients with Parkinson’s Disease (PD). In this case, the electrode positioning precision is very sensitive and correlated to the medical imaging error. This uncertainty mainly stems from MRI distortions and CT/MRI registration [4]. Nevertheless, evaluating the performance of a registration algorithm is very challenging because of the absence of a ground-truth. To improve the error management during brain surgeries, we propose a model that is able to estimate the error of image registration. This preliminary work focuses on mono-modal registration error estimation (REE) of MR images.

Related work. Very few works are available on this subject in the literature. Pluim et al. pointed out that the creation of a REE method is very challenging [6].

One detailed study proposes a supervised convolutional neural network (CNN) regression model, trained on artificially distorted images in order to estimate lung CT mono-modal registration error [2]. The authors present a model

that is able to output a 3D error map. Their CNN is patch-based, it takes as input the 3D patches of two artificially distorted images, and outputs the magnitude of the difference of these distortions for each voxel.

Additionally, the biomedical domain already benefits from CNN in other applications such as segmentation where the U-Net model is a well-known and recognized approach [7, 8]. Also, U-Net has been used before for medical image registration. For instance, in [3], the authors present a U-Net regression model that is able to learn the 3D transformation necessary to register two intra-patient lung CTs.

Nevertheless, there is no previous study proposing a REE method for brain imagery (MRI or CT). This lack impedes the stereotactic error management.

2 Methods

Our first study is focused on brain MRI mono-modal registration and takes inspiration from some methods applied in the literature [2, 3]. We build a U-Net [7] regression model, that is trained on artificially distorted brain MR images. The data set used for training our model is the BraTS-Reg registration challenge data set [1].

Data set. BraTS-Reg is a multi-site, multi-modal MRI brain data set created for a registration challenge [1]. The data set comprehends a total of 140 patients, for which there are four pre-operative scans (T1, T2, T1 contrast enhanced - T1CE - and FLAIR) with a brain tumor and four follow-up ones after the tumor removal.

Artificial deformations. Eppenhof and Pluim made available an artificial deformation Python library that is capable of applying multiple transformations in the image space and performing only one interpolation at the end to limit the smoothing [3]. With this library, we create non-linear B-spline artificial deformations to train our supervised model. We choose the maximum deformation as 4 mm in order to have similar distortions to the ones induced by MR imaging [5].

Model description. Our U-Net model receives as input a pair of 3D MRIs: the fixed image and the moving image. The fixed image, denoted by $I_F(\mathbf{x})$, is a T1CE pre-operative scan selected from the BraTS-Reg data set. The moving image input, denoted by $I_M(\mathbf{x})$, is obtained from the fixed one by applying a random distort-

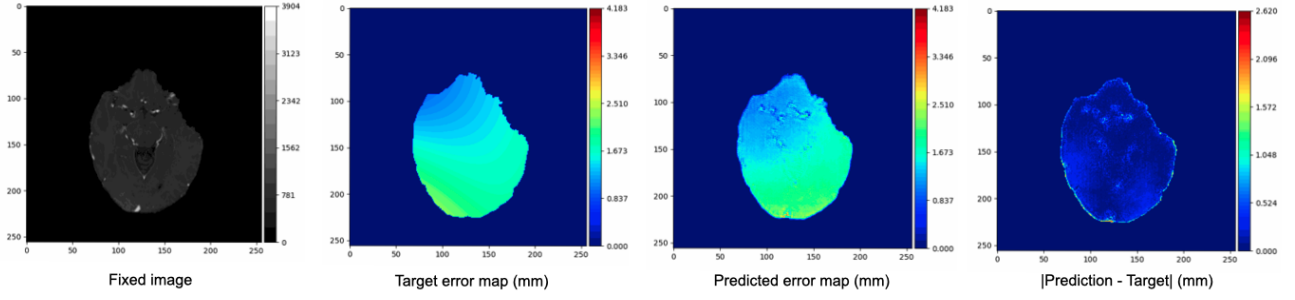


Figure 1: One slice of a MRI volume (input fixed image), target error map, predicted error map, and difference.

tion \mathbf{T}_{dist} : $I_M(\mathbf{x}) = I_F(\mathbf{T}_{dist}(\mathbf{x}))$.

The model is trained with a 3D volume target error map $E_{FM}(\mathbf{x}) = ||T(\mathbf{x}) - \mathbf{x}||$, that shows, for each voxel of the fixed image, how much it is displaced in millimeters in the distorted image. The goal is to learn an error map $\hat{E}_{FM}(\mathbf{x})$ that is close to $E_{FM}(\mathbf{x})$. For that, we train with a L_1 -norm loss function of the difference $\hat{E}_{FM}(\mathbf{x}) - E_{FM}(\mathbf{x})$.

We train the network with the Adam optimizer and a learning rate of 1.0×10^{-4} for 500 epochs.

From the 140 samples of the BraTS-Reg data set, we split it into 20 patients for a test set, 30 for validation and 90 for the training set.

3 Results and Discussion

All results are available at our public repository¹.

By comparing the target error maps artificially generated with the ones predicted from our model, we calculate the map of the absolute difference between the target and the prediction, to measure our algorithm performance. The results for one patient are depicted in Figure 1. The predicted error map shows that the model learns the overall form of the target map. However, it also presents some elements of the brain anatomy directly from the input image. This is likely due to the skip connection mechanism that transfers the input information to the last layers of the network. This hypothesis will be tested in a deeper analysis of the results. The difference error map shows that the error is maximum on the borders of the brain region. This means that the model has difficulties to learn the features from the edge of the brain. The cause of this behavior still needs to be investigated.

In order to measure in millimeters the performance of our model, we calculate the histogram of the difference $\hat{E}_{FM}(\mathbf{x}) - E_{FM}(\mathbf{x})$ for all the patients in the validation set. The histogram has an almost symmetric distribution. The mean of this histogram is -0.0019 mm and its standard deviation is 0.26 mm. Comparing these values with the 1 mm voxel size of the used images and with the current millimetric errors of the stereotactic procedures, we can state that these preliminary results are very promising. Moreover, our results present very similar performance to

the ones obtained in lung CT mono-modal REE in [2]. However, the real stereotactic use-case needs a method that would be adapted to the multi-modal CT/MRI registration. In the next step, we plan to extend our model to predict CT/MRI registration error.

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¹<https://bitbucket.org/leandrorobeaute/orasis-results/src/main/>