Image registration for real-time deep learning-based rigid motion correction at 7T

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Introduction

- Magnetic resonance imaging (MRI) is highly susceptible to motion effects due to long scan times and data acquisition in frequency space. These effects are amplified at 7 Tesla (7T) due to the higher spatial resolution compared to clinical-strength MRI.
- Prospective (real-time) motion correction solutions reduce both scan and post-processing time. One example is multislice prospective acquisition correction, or MS-PACE, introduced by Hoinkiss et al. for 3T fMRI and extended to 7T by Winata [1,2].
- Replacing MS-PACE's rigid-body image registration with deep motion parameter prediction can reduce scan times even further. Early work on reproducing the image registration method and plans for model development are presented here.

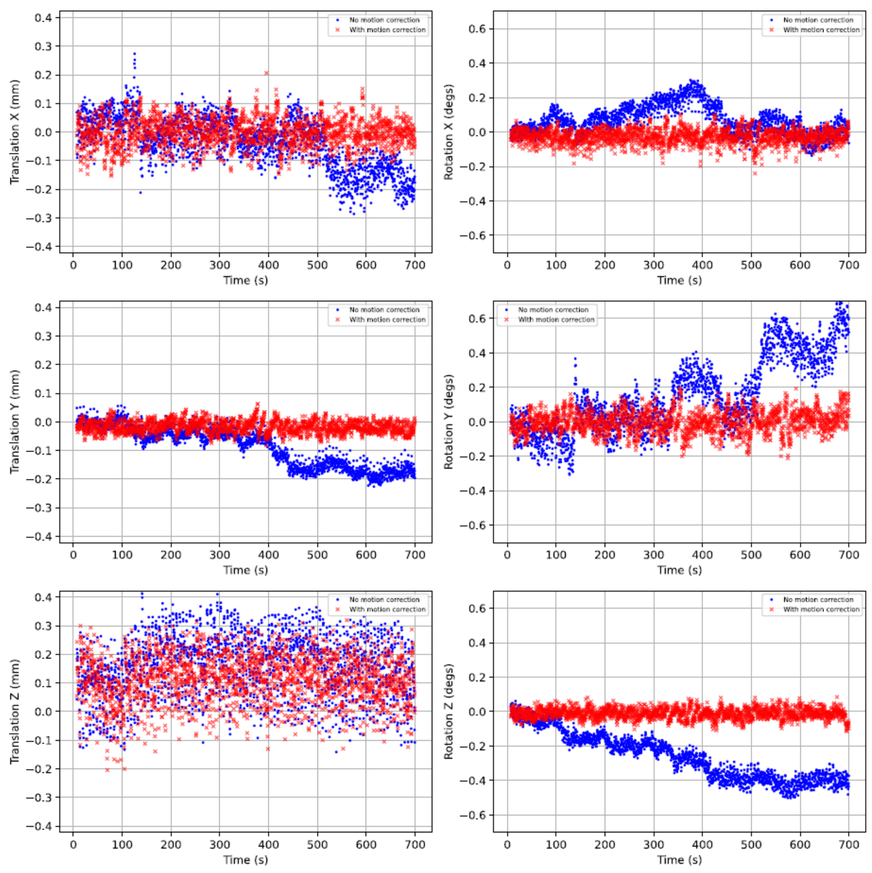


Fig 1. Retrospectively-calculated rigid-body motion parameters from one subject scanned with (red) and without (blue) real-time motion correction. Image from Winata (2023) [2].

Results

The reproduced image registration method using SimpleITK did not perform to the same standard as the original ICE method; the Mutual Information metric did not converge during optimization (Fig. 2), and the motion parameter outputs were inconsistent over different runs. When applied to resting-state fMRI timeseries (Fig. 3), the translation and rotation parameters exceed the expected noise compared to Winata's results in Figure 1.

An example of motion simulation is shown in Figure 4. Figure 5 shows test results from applying *uniGradICON* out of the box, which performs deformable image registration, onto a translated ABIDE EPI volume.

Future work

Image registration using SimpleITK requires further characterization and assessment against the MS-PACE registration method using healthy volunteer data.

A comparison between a *uniGradICON*-derived model and a standard convolutional neural network for rigid-body registration would allow us to have a better understanding of the feasibility, time benefits, and additional hardware requirements of a foundation model-based prospective motion correction method.

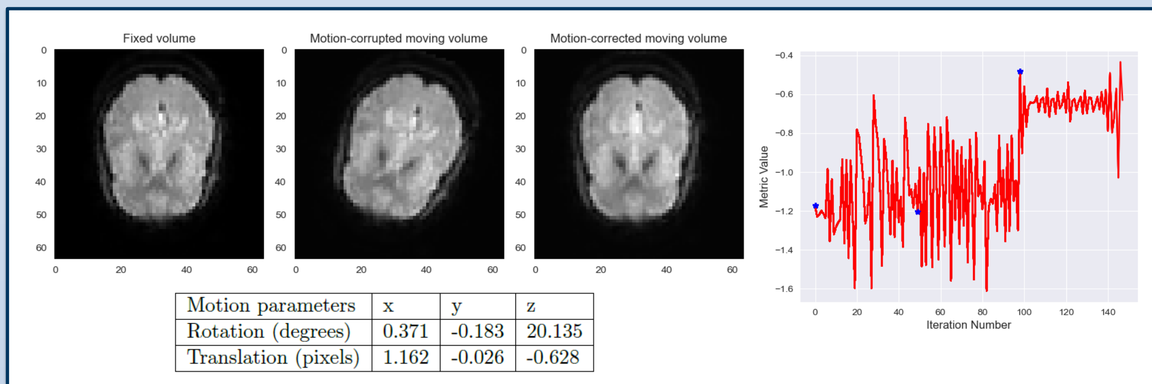
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Methods

- Equipment: Jupyter Notebook, Siemens' Image Calculation Environment (ICE), SimpleITK (simplified interface of Insight Toolkit).
- Dataset: Resting-state fMRI echo-planar imaging (EPI) timeseries from the Autism Brain Imaging Data Exchange (ABIDE) [3].

Image registration: The MS-PACE image registration was reproduced from ICE to Python using SimpleITK. EPI volumes were transformed with rigid 3D parameters and registered back to the original volume. The performance was assessed using Mattes Mutual Information. As a test, an EPI volume was rotated by 20° and registered back to itself. The registration was also performed over entire fMRI timeseries, where each volume is mapped onto the initial volume.

Model training: A training set was prepared by simulating rigid motion in EPI volumes of sub-pixel translations and sub-degree rotations. The foundation model *uniGradICON*, which performs deformable medical image registration, was identified as a candidate for fine-tuning to achieve feature extraction and rigid registration [4].



Motion parameters	x	y	z
Rotation (degrees)	0.371	-0.183	20.135
Translation (pixels)	1.162	-0.026	-0.628

Fig 2. Single volume registration after a -20° rotation. The rotation is accounted for, but the registered volume includes extra translation.

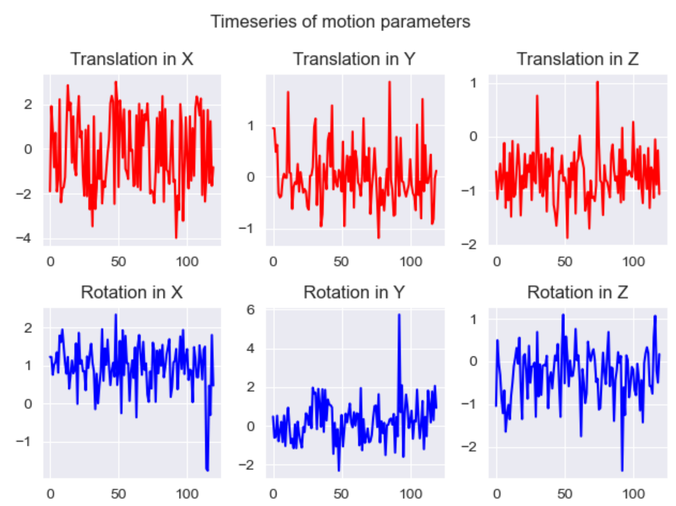


Fig 3. Rigid 3D motion parameters obtained from registration of a resting-state fMRI timeseries. Both translation and rotation values are greater than the noise seen in Figure 1.

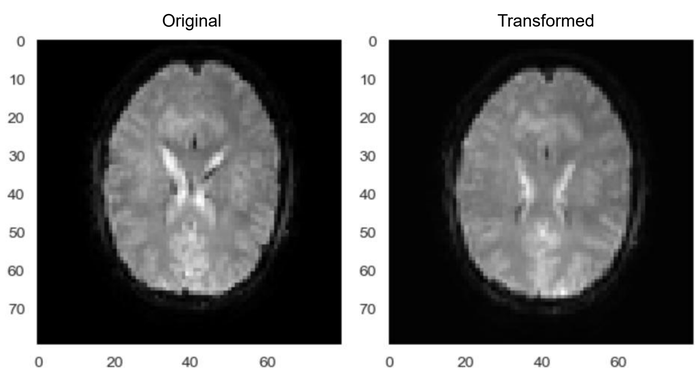


Fig 4. Example of simulating motion in an EPI volume; random translation and rotation values in x, y, and z axes were applied to the original volume on the left and shown on the right.

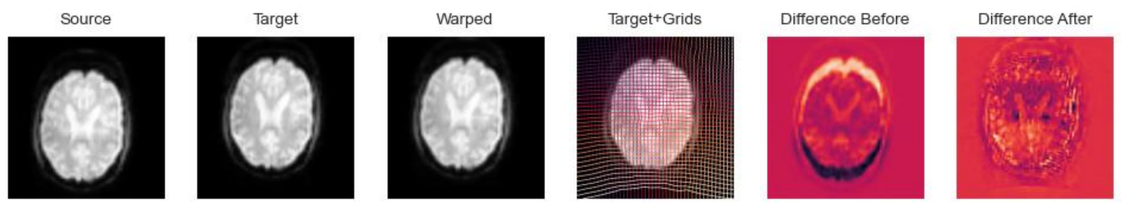


Fig 5. Example of *uniGradICON* results from registering a translated EPI volume onto itself, with a deformation warping grid [4].

References
[1] Hoinkiss et al., Neuroimage, 2009.
[2] Winata, PhD Thesis, 2023.
[3] Di Martino et al., Mol. Psychiatry, 2014.
[4] Tian et al., MICCAI, 2024.