

# Non-rigid Registration of Functional to Anatomical Brain MR Images Using Constrained Optimization

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## Introduction

The results of functional MR brain image analyses are normally reported by overlaying the detected activation maps on high-resolution T1-weighted anatomical images. Brain functional localization is achieved via resampling the functional images into the 3D anatomical image space. In order to correct for the effect of motion, a rigid or affine registration is applied prior to the resampling stage. But due to different sources of nonlinear distortions in fast functional MRI echo planar imaging (EPI), mismatches of a few millimeters may occur even after an accurate affine registration. Nevertheless, finding accurate correspondences between functional and anatomical images is quite challenging, as is evident from the fact that only a few of the limited number of non-rigid registration techniques which have been developed for multi-modality image registration [1] have been applied to the EPI-to-MRI, functional-to-anatomic registration problem [2,3]. In this study, a fully automatic, robust registration algorithm is introduced to accomplish hierarchical rigid and non-rigid transformations based on a bound constrained optimization algorithm [4].

## Methods

The registration technique consists of three major parts: transformation, similarity measure, and optimization. An estimation of Mutual Information (MI) described in [5] has been used as a robust multi-modality intensity-based similarity measure. Two hierarchical transformations, a 6-parameter 3D rigid transformation and a high dimensional non-rigid Free-Form Deformation (FFD) have been used. Rigid registration contributes mainly to motion correction, while non-rigid transformation contributes to spatial distortion correction. A second-order gradient-based Levenberg-Marquadt algorithm has been used for the rigid transformation optimization and a quasi-Newton bound constrained optimization [4] has been utilized to deal with the dimensionality of the large parameter space of the FFD transformation. The FFD transformation has been formulated by a 20x20x20 grid of control points, where each point consists of three displacement parameters. Therefore, the total deformation model has 24000 parameters. In this iterative optimization procedure, the MI similarity measure between the deformed functional image and the reference anatomical image is maximized and the procedure is terminated when the rate of similarity variation becomes less than a tolerance (here,  $1 \times 10^{-5}$  units). Finally, the functional image is resampled using a third-order B-spline interpolation based on the displacement of the nearest 64 control points, similar to deformation resampling [2].

## Results

The algorithm is tested on MR datasets of 6 different subjects obtained with a Siemens Trio 3T scanner. Each dataset includes a high-resolution anatomical image with a spatial resolution of 0.94x0.94x1.30mm and a time series of axial EPI images with a spatial resolution of 3.125x3.125x3mm. A mean image was obtained based on all the EPI images of a time series realigned by using the rigid realignment method in SPM. The mean image was then used as the source image to be registered to the target anatomical image. The most significant nonlinearities in the EPI images were observed to lie in internal brain structures along the anterior-posterior direction. Thus, a bound constraint of 6mm in the coronal slice-rendering direction and 2mm in the other two directions was defined for the optimization of the displacement parameters. The initial rigid registration step is quite fast; the non-rigid registration typically goes through 8 to 12 iterations in less than 30 minutes (on a dual processor 3.2 GHz Linux workstation with 4 GB RAM). Figure 1 shows the diagrams of the maximization and convergence of the MI similarity measure for all of the datasets, and some of the results are shown in Figure 2 for three of the datasets. Selected slices of the brain are presented in axial and sagittal views as follows, from left to right: (1) the source mean EPI image (after rigid registration), (2) the target anatomical image, and (3) the final EPI image (after non-rigid registration).

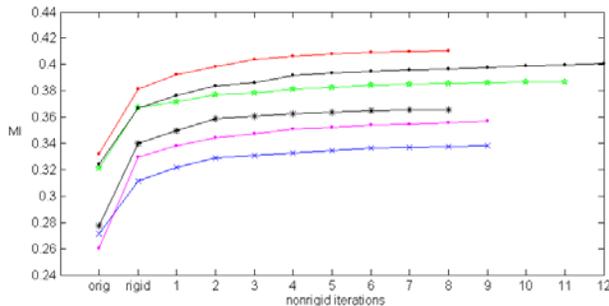


Figure 1: Maximization and convergence of MI similarity measure for all datasets

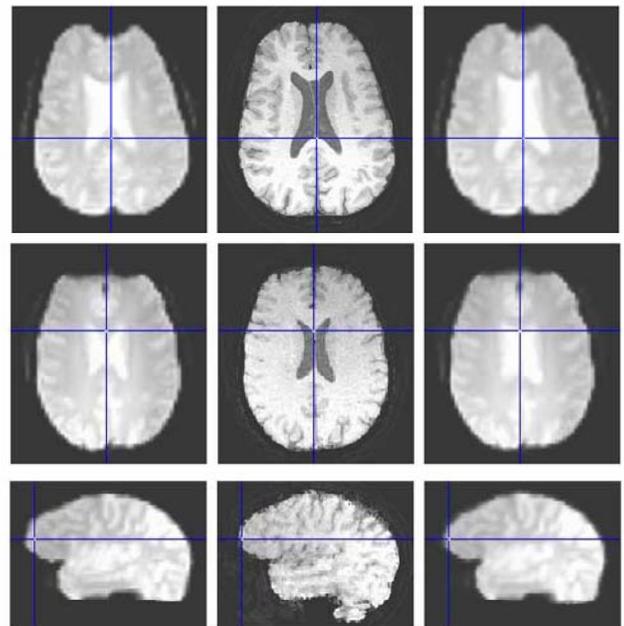


Figure 2: left to right: EPI (after rigid registration), MRI anatomical image, and EPI (after non-rigid registration) of three different datasets

## Discussion

While brain warping has been extensively studied in the literature for registering the brains of different subjects [6], there are only a few studies addressing the development of non-rigid registration techniques for intra-subject functional to anatomical brain image registration [1-3]. Motivation for this development has been spatial distortion correction. While nonlinear distortions are normally observed in fast functional EPI, the complicated relationship of intensity values and the vague brain structures in EPI pose challenges in establishing correspondences between functional and anatomical images. Currently, the functional image analysis packages, such as SPM and FSL, provide only rigid and affine co-registration tools. The technique considered in this study uses the robust MI similarity measure, an optimized grid of control points, and a powerful bound constrained optimization procedure to deal with the above difficulties. The developed registration technique provides practically significant enhancement in functional to anatomical registration.

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**References** - [1] G. Hermosillo et al., *J. Comp. Vis.*, 2002, 50:329 [2] C. Studholme et al., *IEEE TMI*, 2000, 19:1115 [3] M. Otte, *IEEE TMI*, 2001, 20: 193, [4] R. Byrd et al., *SIAM J. Sci. Comp.*, 1995, 16:1190 [5] F. Maes et al., *IEEE TMI*, 1997, 16:187 [6] A. Toga, *Brain Warping*, Academic Press, 1999.