Nonlinear Image Registration in AFNI

Abstract Submission No:

1558

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Introduction:

AFNI is a widely used open source software platform for analysis and display of 2D and 3D MR images and brain activation maps. Previously, AFNI's 3D image registration capabilities were limited to affine and low order polynomial transformations ("warps"). Here, we describe our new implementation of a more general nonlinear registration procedure in the AFNI package.

Methods:

One goal of image registration is to find a spatial warp W(x) such that an image I(x) is transformed to "look like" a base image J(x); that is, I(W(x)) ≈ J(x). A few basic choices have to be made when implementing a code to find W(x) given I(x) and J(x):
(a) How is W(x) defined and computed?
(b) What is meant by the similarity measure "≈"?
(c) How are the parameters that define W(x) optimized, with respect to Question (b)?
Question (a) has many diverse answers. The method chosen in AFNI is to define W(x) as the composition of a sequence of elementary warps: W(x) = E_1(E_2 (... (E_n(x)) ...)). An elementary warp E(x) is defined as being the identity transformation E(x)=x, *except* over a 3D rectangular patch, where E(x) is the identity *plus* the sum of 24 C^1 Hermite cubic polynomial basis functions. The magnitudes of the coefficients of these basis functions are limited to ensure that E(x) is invertible.

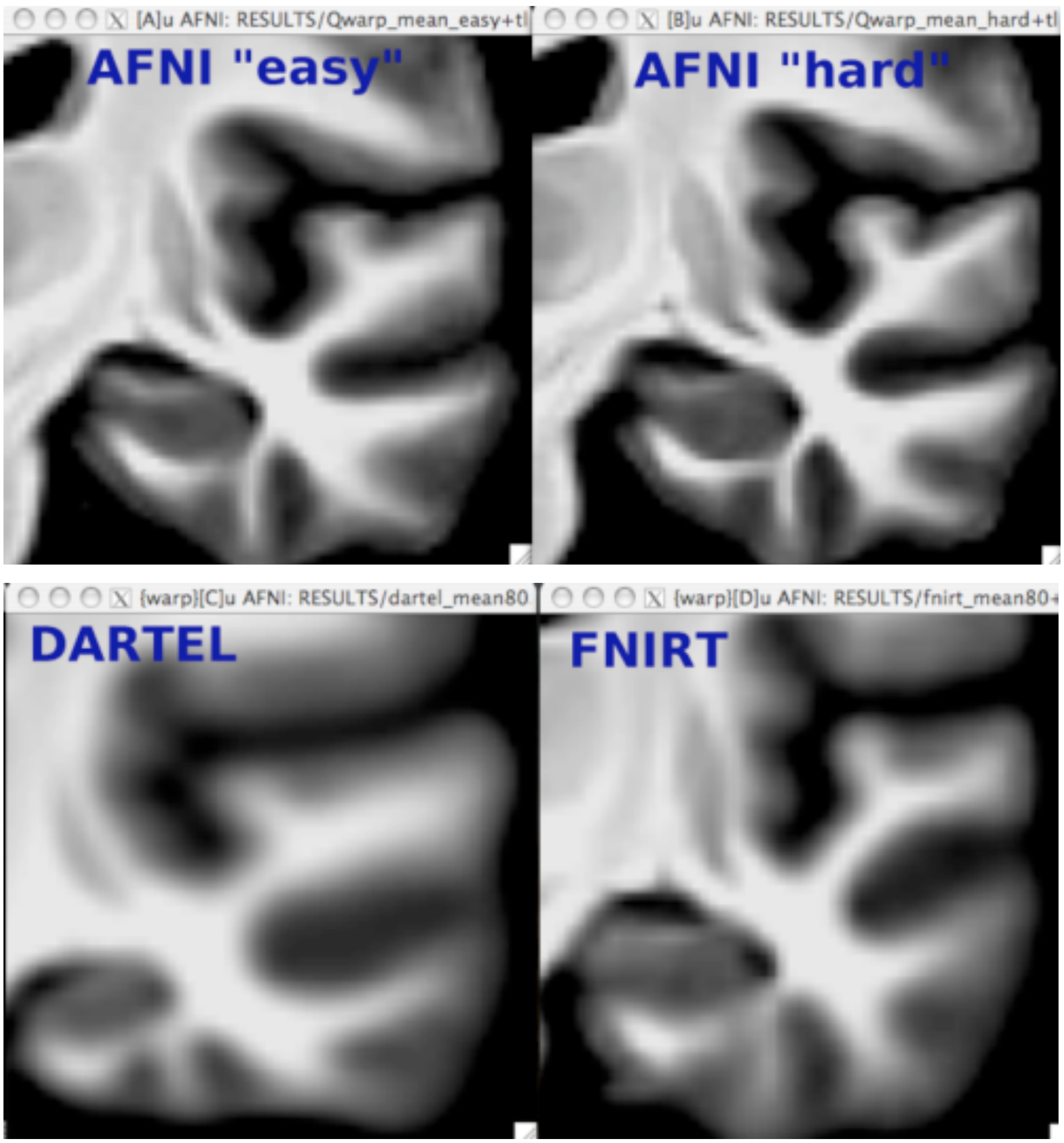
W(x) is stored as a set of displacements on the 3D grid: W(x) = x+D(x) (identity has D=0) . A patch is selected, and the 24 parameters in a new E(x) are optimized so that W_{new}(x) = W_{old}(E(x)) provides a better match between I(x) and J(x). Once these parameters are optimized, the resulting W_{new}(x) becomes W_{old}(x), a new patch is selected, etc. Since the elementary warps are C^1 and invertible, the resulting warp is a grid representation of a diffeomorphism. A neo-Hookean strain-energy penalty is used to ensure W(x) doesn't become "weird".

The initial patch size is the entire 3D volume enclosing the base image J(x). Then the patch sizes systematically shrink by a factor of 0.75 at each step, and the patches are scanned over the volume (with 50% overlap). The finest patch size is controlled by the user; the default final level is 25 voxels on an edge, but as small as 9 voxels (cubed) is allowed. In the default "easy" (or fast) mode of operation, 1 optimization pass is made for each patch. In the "hard" (or slow) mode of operation, 2 optimization passes (2 E(x) warps) are made for each patch. Optimization is done via the Powell NEWUOA method.

The new AFNI program *3dQwarp* implements the algorithm outlined above, using several definitions of "≈". Utility program *3dNwarpCalc* can do various operations on 3D warps stored as displacements; for example, inversion, composition, and square root: R(x) such that W(x)=R(R(x)). Program *3dNwarpApply* takes a 3D warp and applies it to transform another dataset. One principal application of this code is to warp brain maps, after using structural images to determine the nonlinear warps to a common space.

Results:

Eighty 3T T1-weighted structural volumes were selected from the FCON-1000 collection. These volumes were skull stripped and aligned using affine transformations to Talairach-Tournoux (TT) space. Each one was then registered via *3dQwarp* to the N27 T1-weighted template, as transformed to TT space. The "easy" results were refined to a patch size of 25 voxels (13 mins); the "hard" results to a patch size of 11 voxels (52 mins). FNIRT and DARTEL were also applied to these 80 datasets. The temporal lobe results below are the averages of these registered volumes.



Conclusions:

3dQwarp provides an effective tool for nonlinear registration of 3D images inside AFNI. It is being applied to group studies and also to individual pre- and post-surgical studies, and will be incorporated into AFNI's workflow. "Hard" work gives slightly sharper results than "easy"'; both modes are (at least) comparable to alternatives.

Modeling and Analysis Methods:

Image Registration and Computational Anatomy