3D rigid body motion correction in k-space

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Introduction: Motion correction of fMRI data is a fundamental step to be performed prior to functional analysis: even subvoxel motion dramatically corrupts the BOLD signal, invalidating the assumption that intensity variation in time is primarily caused by neuronal activity. Unlike the most widely used applications such as AFNI and SPM that operate in the image domain, the algorithm presented here corrects rigid-body motion in the three spatial dimensions by operating in the Fourier domain, thus decoupling and independently correcting rotation and translation effects.

Method: The principles for performing 3D rigid body motion correction in the Fourier domain can be thought of as an extension of the basic concepts exploited by the in-plane registration algorithm DART (Maas et al., MRM 37:131-139).

In 2D, if an image in real space is rotated about an arbitrary center of rotation, then the magnitude data of its Fourier transform is simply rotated about the origin of the Cartesian axes, through the same angle as in real space (Fig.1 – left: images; right: magnitude of the Fourier transform). Similarly, in 3D, rotations between the two volumes to be aligned are visible in the 3D-FFT magnitude data, where no contribution from translational effects is present. Since rotations in k-space are always about the origin of the Cartesian axes, we estimate them by aligning the "topography" of the surfaces of spherical shells (of equal radius and centered at the origin), encoding magnitude Fourier data of the volumes to be registered (Fig.2). After the rotation angles have been estimated, the test volume is rotated by the same angles in image-space.

At this point, rotation effect is removed, and only translations need to be corrected. Since a shift along any spatial axis introduces a linear phase change along the respective frequency axis (Fourier shift theorem), linear translations can be estimated by considering the cross-power spectrum (CPS) of the original and the translated image. In 2D, the phase of the CPS will result in a tilted plane, whose slopes along X and Y hold the information about translation (Fig.3). In 3D, translation correction is achieved by fitting a hyper-plane to the phase of the CPS, adding it to the Fourier transform of the test image, and finally inverse Fourier-transform the result. The method is non-iterative, thus very efficient, and can accurately detect sub-voxel translations.

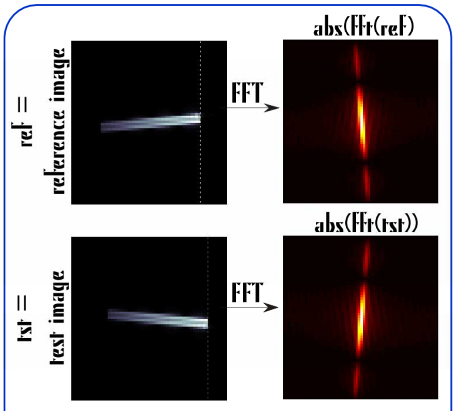


Figure 1.

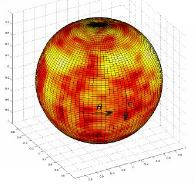


Figure 2.

angle{CPS} =
angle { fft(ref) · conj(fft(tst$_{RC}$)) }

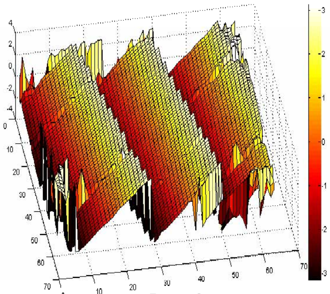
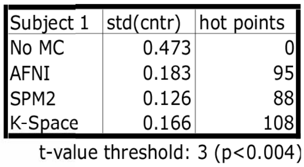


Figure 3.



Subject 1	std(cntr)	hot points
No MC	0.473	0
AFNI	0.183	95
SPM2	0.126	88
K-Space	0.166	108

t-value threshold: 3 (p<0.004)

Figure 4.

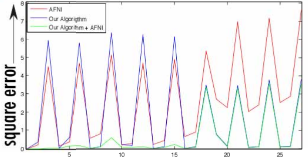


Figure 5.

Results: The algorithm was implemented in MATLAB, and tested on both synthetic and real EPI time series covering the whole brain. We compared our results to the registered data obtained with two widely used algorithms, namely AFNI and SPM2. Image-space methods estimate simultaneously the 6 parameters that describe the rigid-body motion, thus increasing the risk of locking to a local minimum of the cost function (the squared difference of the two volumes), while our algorithm, estimating the 3 rotation parameters and the 3 translation coefficients in two separate steps, appears to be more accurate.

Analysis of real fMRI data revealed that our method leads to a higher number of activated voxels in a t-test in case of experiments affected by a big amount of motion, while, in case of very small head movements, the image-space-based method implemented in the AFNI package provides better statistical results. In Fig.4, we show the results of an auditory experiment, in which the subject's head motion was significant. The center of mass of the brain appears to be more stable over time when the time course is registered using SPM2, but our k-space method provides the highest number of active voxels in a t-test. We believe that this higher number of active voxels is due to better registration, and not to a smoothing effect introduced by motion correction, because our algorithm uses Fourier interpolation, which has been proven to minimize smoothing.

Moreover, square-error measurements in simulated data suggest that better volume registration can be achieved by means of serial application of motion correction first in k-space and then in image-space, the former step being more robust to local minima and correcting for larger motions, and the latter seeming more suitable for a fine correction. In Fig.5 we show the squared difference between the reference and 27 volumes affected by different amount of motion (volumes 17-27 being affected by bigger motion). The better performance of the serial application of the k-space method and an image-space method is clear (green plot).