Evidence for systematic within-subject head motion in fMRI and its measurement with maximum voxel displacement

M. C. Fazeli^{1,2} and S. Strother^{1,2}

¹Rotman Research Institute, Baycrest Center, Toronto, Ontario, Canada, ²Medical Biophysics, University of Toronto, Toronto, Ontario, Canada

Introduction: There are no standard approaches for combined assessment of the 6 rigid-body parameters used to estimate withinsubject motion in fMRI. This is particularly a problem when comparing the different scales of rotation (degrees) and translation (mm) parameters. As a result, quality control of within-subject alignment is quite variable between, and even within research groups. We present a single metric based on maximum voxel displacement (maxdisp, mm) for combining the 6 rigid-body motion parameter estimates (MPE) to gauge the extent of head motion in fMRI experiments [1]. We used Singular Value Decomposition (SVD) to study the systematic structure of the MPEs produced by AFNI for young and old subject groups performing multiple tasks. We show that calculating maxdisp for each volume in a time-series can effectively summarize much of the systematic MPE structure based on our SVD results. Therefore, maxdisp provides a single metric for quick assessment of estimated head motion during an experiment, which may be more effectively thresholded during quality control than the original MPEs.

Methods: Our data consisted of 10 young (18-30) and 10 old (> 65 years) normal subjects who performed 4 encoding and 2 recognition memory tasks (6 runs (tasks) / subject) in an fMRI block design at 1.5T [2]. This data had already been visually screened for no obvious movement greater than approximately 3mm (1 voxel). The data was within-subject aligned to the tenth volume of the first task of each subject using AFNI's 3dvolreg algorithm with Fourier interpolation. Time-series for the 6 rigid-body MPEs and maxdisp were output for each subject and task. Each of the 60 (10 subjects x 6 tasks) MPE time-series (roll, pitch, yaw, z, x, y) was run-mean subtracted and decomposed using SVD. Each SVD component contains an eigenvalue (i.e. total component variance), eigentime-series, and 6 eigenweights indicating the relative extent to which each rigid-body parameter contributes to the time-series. Boxplots of the distribution of eigenspectra values and eigenweights across the 60 runs were produced for both young and old groups.

Results: The eigenspectra for both young and old subjects showed that on average, the MPE time-series structure is not random and falls within the first two components (Young: C1 μ =77%, C2 μ =14%; Old: C1 μ =70%, C2 μ =20%). Boxplots of the pitch and z eigenweights show a much wider ± spread and larger zero-offset in the first component (particularly for the old group) and a much wider ± spread in the second component. This finding was most pronounced in the recognition tasks that were almost twice as long as the encoding tasks, and were placed as the final 2 tasks / subject. This indicates that subjects move primarily in the pitch (head-nod) and z (in/out of the scanner) directions and tend to move more the longer they are in the scanner. The first component time-series showed a gradual linear movement trend over time, while the second component's eigenweights were identified: 15 largest negative (< Q1) and 15 largest positive (> Q3). For young and old groups, 9 and 8 runs had both large pitch and z movement eigenweights respectively. As a result, our analysis includes 51 and 52 runs, and all 10 subjects from each age group respectively. Each of these runs had its raw pitch and z time-series correlated with its maxdisp time-series; the figure shows the correlation for each group of 15 runs (per quartile) in both young and old subjects. The young show higher median correlation coefficient (cc) values particularly for pitch, which appears to most strongly influence maxdisp. Maxdisp provides a reasonable MPE summary for 37 and 35 runs with cc > 0.7 in young and old groups respectively. We are currently studying those runs with cc < 0.7 and why maxdisp does not appear to adequately capture particular z motions.

Conclusions: Using SVD, we have demonstrated that there is systematic structure in rigid-body motion parameter estimates that can quite often be summarized by a maximum voxel displacement time-series. This can be used by researchers to assess the effects of motion on their fMRI data without having to deal with the disparate units of motion parameter estimates. Furthermore, we have shown that subjects tend to gradually move in the pitch and z direction, especially with longer scan times. Maximum voxel displacement may therefore be useful as a quality control method for tracking motion in real-time, and can potentially be used to build a predictive model to identify and reduce head motion during a scan.

References:

Strother et al., J Comput Assist Tomogr, 1994 Nov-Dec;18(6):954-62
Grady et al., J Cog NeuroSci, 2006 18(2):227-241

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