# Evaluating strategies to deal with motion in fMRI using Independent Component Analysis

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**Introduction:** Motion is one of the most common causes of fMRI failure [1]. SPM2 [2] attempts to address the problem by realigning the image data to a reference image before undertaking an analysis. During analysis it is also possible to add the motion correction parameters estimated by the least square realignment as covariates of no interest. If one includes motion covariates in General Linear Model (GLM), and motion is correlated with the block paradigm, one can expect a loss of true activation and a rise in motion-induced activation. More recently, it has been noted that data-driven methods can identify and remove artifactual sources of variance within fMRI datasets. In the present study we investigated whether it is possible to identify the signal change in fMRI time series due to motion with Independent Component Analysis (ICA) and then remove them. Specifically, we wished to determine, using simulated and real data, whether ICA could outperform standard approaches, as assessed using receiver operator characteristic (ROC) curves as well as the maximum t-score.

**Methods:** The ICA-analysis and removal of components were carried out using GIFT [3].Three different methods are suggested. The results from these methods were compared to the result from SPM analysis with and without motion covariates (+mc and –mc). The first method (ICA1) selected and removed the component with highest correlation to motion. The second method (ICA2) removed all components with a correlation coefficient higher than a set threshold (0.3). The final method (ICA3) discarded all components that had a correlation to motion higher than 0.3, together with a correlation to the expected task response less than 0.3. Following removal of motion-related components, the data were remixed, and a standard SPM analysis performed, where motion parameters were included as covariates.

Simulated data: To generate the simulated data, one normalized image was replicated to a total of 90 images, and then gaussian noise (2.5% of mean signal) was added. Activation was added as three spheres with relative weights of 1, 0.8 and 0.6. Motion with known size and correlation (to the expected response) was added.

Patient data: 34 volunteers performed a language study, with the following parameters: 16 subjects (TR: 3.6 seconds, flip= $60^o$, res: 128x128, total of 90 scans, slice thickness: 4 mm, pixel size (x,y) 1,88 mm). 18 subjects (TR: 3,2 seconds, flip: $75^o$, 64x64, number of scans vary from 107 - 111, slice thickness: 3 mm, pixel size (x,y)3,45 mm).

**Results:** Results from the simulation were evaluated using two different approaches. The first approach used the ratio between maximum t-values of brain voxels inside and outside the ROI (corresponding to the ground truth).

In the second approach we calculated the True Positive Fraction (TPF) and False Positive Fraction (FPF) within brain voxels and plot them in an ROC-curve. The area under the ROC and size of the t-quotient for each method describes how well the method performed in separating true activation from the motion induced activation. Results from simulated data are displayed below in figure 1. Results indicate that –mc is superior when motion is low or moderate and when motion is high –mc is the worst performing approach. +mc and ICA show similar results for all simulated data. Data suggest that the level of correlation between motion and the task stimuli have no not affect on the choice of optimal processing method.

Patient data were evaluated by measuring highest t-value inside a ROI placed over brain regions were we expected to find true activation, and outside ROI. These results are displayed in figure 2 for eight patients. It is seen that the +mc and ICA1 methods show very similar results for all subjects. In four subjects, the –mc outperforms the other methods, in two it underperforms the other methods, and in two it is the same.

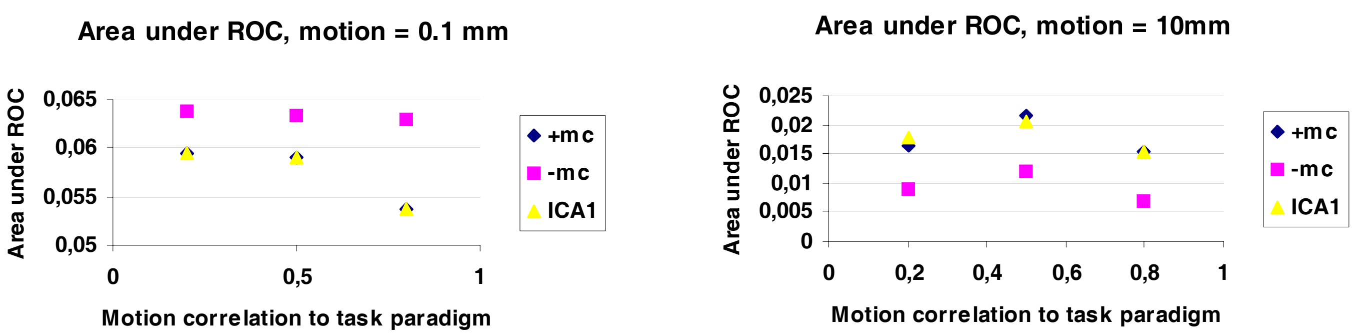


*Figure 1. Results from simulated* ***data****: Relative performance of three motion correction strategies. Left panel: 0.1mm x-translation. Right panel: 10mm x-translation*

**Discussion:**

Results from simulation suggest that SPM analysis without motion covariates is preferred when motion is moderate in size. When the amplitude of the motion increases one sees a decrease in efficiency in all methods but particularly in SPM without motion covariates. It also suggests that method performance is independent of motion correlation.

Real data shows that -mc outperforms the other methods for 4 subjects, underperforms in 2 and is the same in 2. +mc and ICA show similar results for all subjects.

Both simulated data and patient data indicate that the issue of which motion correction strategy is optimal appears to be subject dependent, meaning there is no method that is optimal under all circumstances. Further study is required to answer these issues.

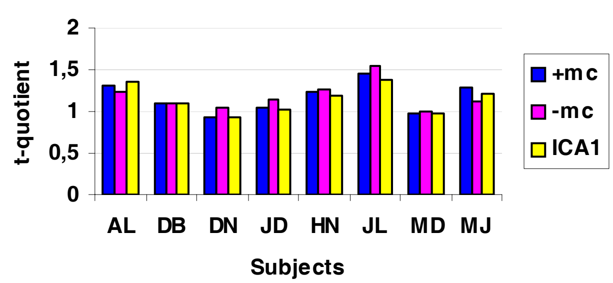


*Figure 2, Results from patient data. Ratio between highest t-value inside ROI and highest outside. Summary data is displayed for eight patients and for three models.*

**References:**

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