Quantification of motion-related artifacts in simulated FMRI data using ICA

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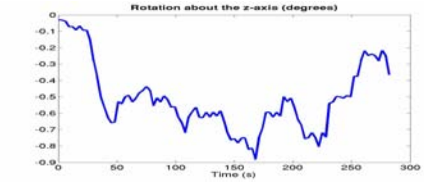
Introduction: FMRI data contain many motion-related artefacts which can limit its usefulness. Many approaches exist to correct for rigid-body motion effects but they struggle to do so in cases when motion has more complex impact on the data (e.g. interaction of motion and the Bo field inhomogeneities). Independent Data Component Analysis (ICA) on FMRI data can be used to spatially and temporally identify these artefacts. However, the accuracy and usefulness of ICA for motion artefact identification and quantification needs to be tested with data which contains realistic artefacts and for which the ground truth is known. Such data can be generated using a recently developed FMRI simulator (POSSUM).We generate data that includes rigid-body motion effects for in-plane rotations, including the interactions with B0 inhomogeneities.

Methods: The FMRI simulator [1] solves the Bloch equations for a voxel-based object model. Motion parameters (three translations and three rotations), gradient and RF fields and T2* variation can all be specified as functions of time (and space for T2*). This allows a wide variety of pulse sequences and signals to be modeled. In particular, the T2* changes can model both desired neuronal activation signals (via the BOLD effect) as well as unwanted physiological changes (e.g. low frequency networks or ``resting states''). More details can be found in Drobnjak and Jenkinson [1].



The data was simulated using an EPI pulse sequence with 4mm in-plane resolution (64x64 voxels), nine 3mm slices, TR=3s, TE=30ms for 98 volumes. The BrainWeb partial volume tissue estimates [2] was used as the object model. T2* time courses were derived from an experimentally acquired FMRI data set. The BOLD changes modelled by this T2* change include stimulus-related activations as well as those of no interest (``physiological noise''). Fig. 1 shows the change in motion parameter (rotation about the z-axis – up to 0.8 degrees) over time. Four separate simulations were generated: (1) no motion; (2) motion represented in Fig. 1 – an average of 0.046 degrees per TR; (3) three times this motion – 0.138 deg/TR; and (4) five times this motion – 0.23 deg/TR. Rician noise was added to all of the simulation outputs and a motion correction algorithm (MCFLIRT), was applied to all of them [4]. ICA was carried out using MELODIC [3].

Results: Figs 2a and 2b show two example components due to motion. Both of the components show effects of the global rotational motion as well as the motion-B0 field interaction, which can be seen around the edges of the brain and the B0-effected areas. The first component shows more localization in the B0-affected areas and therefore is predominantly associated with the motion-B0 interactions. Furthermore, the time courses of the two components are different, as the first closely resembles the original input motion, while the second one does not. This suggests that the influence of the motion on the data is much more complex and does not have a simple relationship with the motion parameter time-course. In Fig 2c the total standard deviation explained by the ICA components in the 4 datasets can be seen. This shows that the non-motion related components had a very similar standard deviation in each case, while the level of residual motion artefact (after motion correction) increased steadily with increasing motion levels. Similarly the number of estimated ICA components was increasing with increasing motion. Furthermore, the non-motion-related ICs are consistently estimated in each case, as shown by the correlations between them in Table 1. Rows 2, 3, 4 of this table show correlation coefficients of the non-motion data with the three motion-corrupted datasets (ascending motion levels).

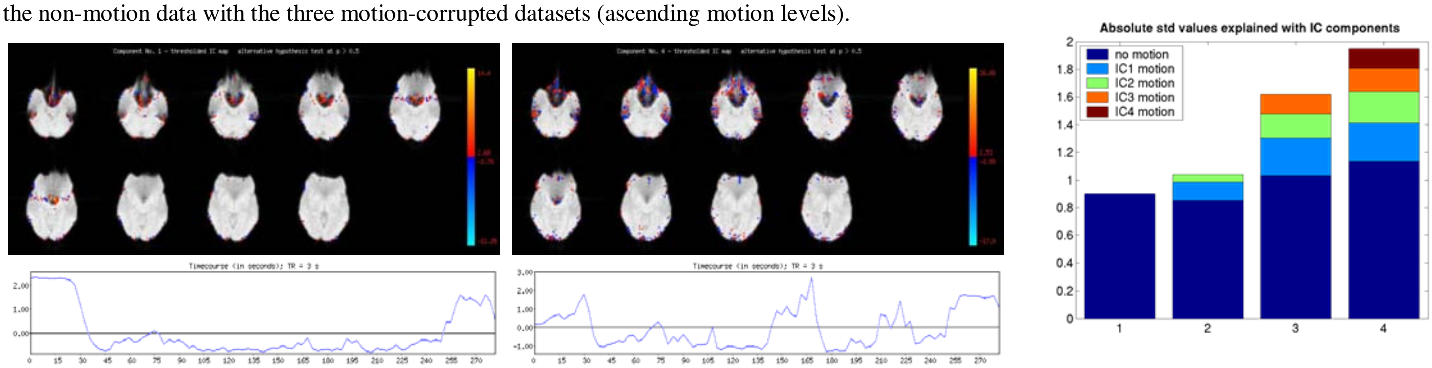


Figure 2 a) An Independent Component (IC) with predominantly motion-Bo effect **b)** An IC predominantly showing the effects of global rotational motion.**c)** A bar-chart which shows the absolute value of the total standard deviation (std) in the simulated data. The four bars represent std explained with ICs found from the four simulations (average motion levels of: 0 deg/TR; 0.046 deg/TR; 0.138 deg/TR; and 0.23 deg/TR). Dark blue bars represent the std associated with all the non-motion-related IC components, while light blue, green, orange and brown bars represent the std of individual motion-related ICs.

IC1	IC2	IC3	IC4	IC5	IC6	IC7	IC8	IC9	IC10	IC11	IC12	IC13	IC14
0.0	0.8	0.83	0.79	0.72	0.77	0.64	0.62	0.47	0.75	0.68	0.21	0.29	0.58
0.2	0.7	0.77	0.60	0.43	0.60	0.49	0.58	0.46	0.61	0.45	0.2	0.37	0.33
0.3	0.5	0.69	0.39	0.39	0.51	0.26	0.5	0.24	0.52	0.33	0.11	0.38	0.34

Table1. The table is showing the correlation coefficients between thresholded IC spatial maps for the non-motion data set and the 3 motion-effected data sets. Only IC1 shows poor correlation since it had similar spatial and temporal characteristics as the motion components and was not effectively separated from the motion components. Note that a correlation value of 0.2 or higher has less than a 0.01 probability of occurring by chance (based on Fisher's r-to-z transformation).

Conclusion: Degraded quality of FMR images due to motion is often observed in the real experiments [5] (e.g. in patients) and is hard to correct, making FMRI less reliable than often required in clinical practice. We have showed quantitatively how ICA can be used to identify motion-related components, how the variation (std) of these components is related to amount of motion, and how the temporal characteristics of some of the motion components is not linearly related to the motion parameter changes. Furthermore, we have shown that the remaining, non-motion-related components are reliably estimated even when large amounts of motion are present. The complicated relationship between motion-artefact and motion parameters can only be explored because of the use of a physically realistic and sophisticated simulation tool (POSSUM). This complicated relationship also demonstrates that simple motion-artefact-reduction (e.g. using motion parameters as regressors) is not sufficient to correct for such artefacts.

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References: [1] Drobnjak and Jenkinson, ISMRM 2004 ;[2] Collins et.al. IEEE Tr Med Im 1998;[3] Beckmann et. al.IEEE TMI 2004;[4] Bannister et al HBM 2001 [5] Hajnal et al MRM 1994