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 B0 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-affected 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. ICA was used to identify the ICs found in the motion data. The authors wish to thank UK MIAS/IRC, UK EPSRC and BBSRC for funding.

Conclusion: Degraded quality of FMRI 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 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).

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