AUTOMATIC SELECTION OF ARTIFACT COMPONENTS VIA RESIDUAL K0 PHASE

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Introduction: Independent Component Analysis (ICA) is a powerful tool for identification and filtering of confound signals in BOLD fMRI. For many fMRI analyses, it has become common practice to run an ICA to capture artifact signals resulting from residual and/or non-rigid motion, as well as more subtle but equally important signals such as those from respiration, cardiac motion, and brain pulsatility. These signals, if found by ICA can be subsequently removed from the data. Examination and selection of suspect components is a time consuming process, susceptible to operator error and bias. As such, several complimentary automated techniques have been proposed to address this problem. Common to all approaches is the implicit a-priori knowledge that unwanted signals have specific, classifiable features such as frequency response and spatial localization.

Using knowledge of the EPI acquisition and reconstruction processes, we propose a method for extracting a reference signal from the EPI time series for subsequent automatic identification (and correction) of artifact.

With dedicated, form-fitting receiver coils with large numbers of elements becoming common place in BOLD-fMRI studies, signal changes due to small motion become more prominent. This is typically a confounding factor during the image reconstruction process where one wishes to detect (for instance) what the true global B_0 offset was. Here, we make the observation that because of the compromises made in reconstructing this type of multi-channel EPI data, a small non-zero residual phase is detectable. This signal is almost entirely related to asymmetric, localized changes in the B_0 field, and provides an integrated, time-locked reference for some of the artefact and motion that is present.

In summary, we propose that by using the zero-order phase information from the complex-valued fMRI time series, each functional run can provide an intrinsic classifier for the ICs.

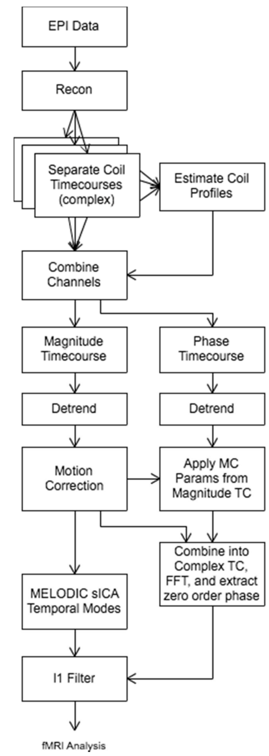

Figure 1: Data pipeline

Methods: EPI data from a visual task BOLD fMRI dataset were used to test this method. Data were acquired from a 7T MRI scanner at 1.1mm^2 in-plane resolution x 2mm slice thickness, 30 axial-oblique slices covering the primary visual area. TE=22ms, TR=2s, GRAPPA R=3. A 23 channel close-fitting receiver coil was used for signal acquisition.

As illustrated in the diagram in Figure 1, data were reconstructed with navigator correction and combined into magnitude and phase time-courses. Data were motion corrected using the FSL[1] mcFlirt tool, detrended, and each volume was then fourier transformed (in space) to estimate the residual k_0 phase timecourse for the artifact reference. Magnitude data were then processed with MELODIC[2] to generate an ICA decomposition. IC timecourses were then used as a basis, A, to fit the confound signal, y, in a l_1-regularized framework:

$$\min \|Ax - y\|_2^2 + \lambda \|x\|_1$$

Seleted components are then removed via FSL regfilt.

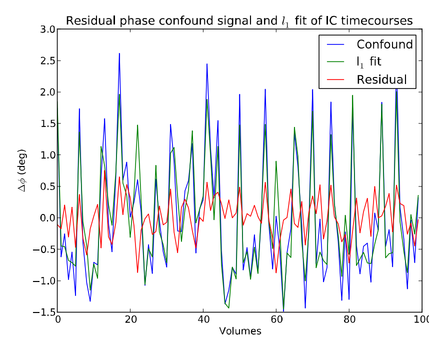

Figure 2: Example timecourse and fit

Results: Figure 2 illustrates a sample phase timecourse, as well as the best fitting subset of selected ICs. Most major features are found through the ICA basis. The l_1 norm contraint promotes sparsity in IC selection and avoids overfitting. Figure 3 illustrates the temporal standard deviations in two slices of the dataset before and after removal of the identified ICs. In this dataset, most of the detected artifact components were related to the subject clenching their jaw, as well as some residual respiratory related motion.

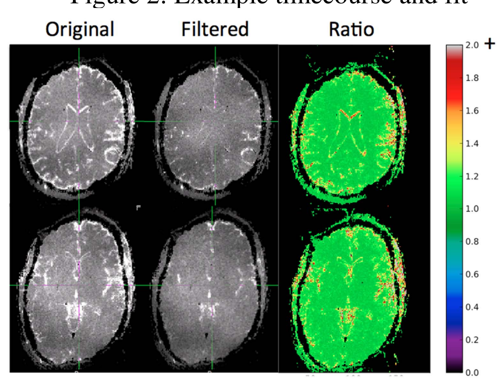

Figure 3: temporal standard deviation maps of two exemplar slices before and after filtering.

Conclusion & Discussion: The use of the residual phase timecourse to drive ICA selection is a promising, data driven method that can compliment current artifact filtering techniques. While some current IC selection methods typically select based on IC correlation with some reference[3], here the novel use of l_1 regularized least squares for selection is an important step in ensuring quality of component selection. As with any ICA based filtering method, the quality of the artifact removal is strongly dependant on the ICA decomposition, and as such, future work will involve examining the robustness of this approach.

References: [1] Jenkinson *et al*., Neuroimage (2012) 62 pp. 782-90 [2] Beckmann and Smith, IEEE TMI (2004) 23 pp. 137-52 [3] Perlbarg *et al.,* Mag Res Imag (2007) 25 pp. 35-46