Volumetric Space–Time Structure of Physiological Noise in BOLD fMRI

Arno Solin[1], Simo Särkkä[1], Aapo Nummenmaa[2], Aki Vehtari[1], Toni Auranen[3], Simo Vanni[3,4], and Fa-Hsuan Lin[1,5]

[1]Department of Biomedical Engineering and Computational Science, Aalto University, Espoo, Finland, [2]Athinoula A. Martinos Center for Biomedical Imaging, Massachusetts General Hospital, Boston, MA, United States, [3]Advanced Magnetic Imaging Centre, Aalto University, Espoo, Finland, [4]Brain Research Unit, O.V. Lounasmaa Laboratory, Aalto University, Espoo, Finland, [5]Institute of Biomedical Engineering, National Taiwan University, Taipei, Taiwan

TARGET AUDIENCE

These methods and results are of interest to researchers aiming to improve the signal-to-noise ratio of their data by removal of physiological noise, and to scientists trying to improve the spatial and temporal resolution of their functional MRI data reconstruction. Furthermore, the results indicate correlation effects between brain regions, which are important to account for in functional connectivity studies.

PURPOSE

To improve the signal-to-noise ratio in functional MRI, accurate treatment of various noise sources is turning vital [1]. This applies especially to the physiological non-white noise components. Even though it has been known for long that cardiac and respiration related physiological noises are structured in space and time [2], this information has not been fully utilized in noise elimination or signal reconstruction. In our study, we aim to estimate volumetric amplitude and latency maps that tell the strength and relative phase shift of the physiological noise oscillations compared to an external physiological reference signal. We present proof-of-concept maps for one test subject, and discuss how this prior information can be applied to removal or estimation of quickly varying noise components in slow fMRI, and utilized in future fast-imaging techniques.

METHODS

We use the Bayesian model based DRIFTER method [3] for separation of the physiological noises from other signal components by accurately modeling the temporal structure of the data using stochastic resonator models. External reference signals and the interacting multiple model (IMM) algorithm are used for extracting the frequencies of the physiological phenomena. The Bayesian optimal separation of the components in the functional data is implemented with Kalman filters and smoothers. The lowest frequency components of the oscillators are then converted into analytic signals and spatial regularization is applied in form of a Gaussian smoothing filter [4]. The phase differences of the analytic signals to the external reference at each voxel can then be studied in terms of complex polar coordinates and visualized as magnitude and phase images.

For testing, we used a 27-run set of resting state fMRI data and anatomical images for one volunteer obtained with a 3 T scanner (Siemens Skyra). The sequence parameters were TR: 77 ms; TE: 21 ms; FA: 60 degrees; FOV: 224 mm; matrix size: 64x64; and voxel size 3.5x3.5x6 mm. Each run, roughly 30 s in length, comprised of two slices; one fixed reference slice and the gap size between the slices advancing with run number. Due to technical limitations the reference slice was changed twice in order to achieve full spatial coverage of the brain. The cardiac and respiration reference signals were acquired time-locked to the fMRI data using peripheral (BIOPAC) pulse measure and a respiratory belt, respectively. The sampling frequency of the physiological signals was 1 kHz. We used two harmonic resonators in the DRIFTER algorithm, and their frequencies were estimated from the external cardiac and respiration signals for each run.

RESULTS

Phase shift maps for a selected set of slices are presented in Fig. 1 (cardiac) and Fig. 2 (respiration). A full cycle corresponds to a lag of approximately 0.94 s in the cardiac and 4.2 s in the respiration induced phase maps. The cardiac phase is nearly constant over the cerebral cortex, whereas the respiratory phase follows a more uniform pattern over the whole volume. The reference slices for each run were used to confirm that the approach provides useful estimates. Each run was treated independently and the phase maps showed strong resemblance to each other in all cases.
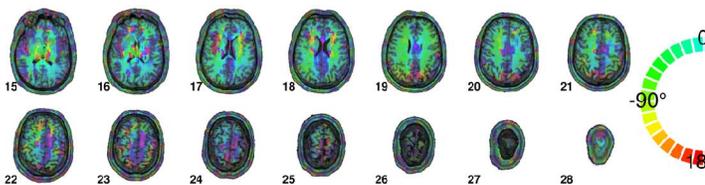
Fig. 1. Temporal phase maps for cardiac noise (slices 15–28).   Fig. 2. Temporal phase maps for respiratory noise (slices 15–28).
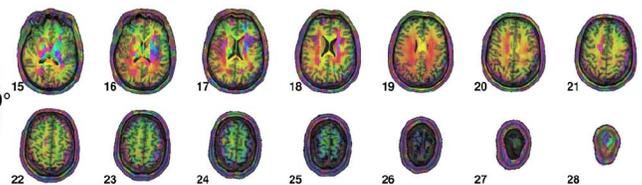
DISCUSSION

The results show that there is a clear phase shift between different areas in the oscillatory noise signals over the whole volume. The presented work generalizes our previous results obtained for two slices [4]. These temporal phase maps can be provided by a reference scan or they can be pre-calculated. Temporal phase level sets (regions oscillating in asynchrony) can catch the physiological noise frequency within slow-sampled data, which makes it unnecessary to capture separate reference signals during data acquisition. For EPI sequences with long TRs, we can combine a priori physiological temporal phase and slice timing information to represent the physiological noise components. The spatio-temporal information of the noise structure could also be used as a priori information in ultra-fast parallel imaging methods (such as [5]).

The non-uniform distributions of physiological noises can be applied in image reconstruction and post-processing to increase CNR, but the results also illustrate the potential importance of our work in functional connectivity analysis. As already discussed in [4], the phase differences of 0, 90, and 180 degrees imply correlation coefficients 1, 0, and –1, respectively. Thus it is essential to properly eliminate the physiological noise sources before connectivity analysis (see, e.g., [6–7]), in order to avoid spurious correlations between brain areas.

CONCLUSIONS

We have presented means to estimate the volumetric spatio-temporal structure of oscillating physiological signals in BOLD fMRI. Proof-of-concept data for one test subject indicates that the phase shift maps can provide substantial prior information in noise elimination and image reconstruction methods.

REFERENCES

[1] Hutton C., Josephs O., Stadler J., et al. The impact of physiological noise correction on fMRI at 7 T. NeuroImage. 2011;57:101–112.

[2] Krüger G., Glover G.H. Physiological noise in oxygenation-sensitive magnetic resonance imaging. MRM. 2001;46:631–637.

[3] Särkkä S., Solin A., Nummenmaa A., et al. Dynamical retrospective filtering of physiological noise in BOLD fMRI: DRIFTER. NeuroImage. 2012;60:1517–1527.

[4] Särkkä S., Solin A., Nummenmaa A., et al. Identification of spatio-temporal oscillatory signal structure in cerebral hemodynamics using DRIFTER. Proc. of ISMRM 2012;20:1535.

[5] Lin F.-H., Wald L.L., Ahlfors S.P., et al. Dynamic magnetic resonance inverse imaging of human brain function. MRM. 2006;56:787–802.

[6] Chang C., Glover G.H. Time–frequency dynamics of resting-state brain connectivity measured with fMRI. NeuroImage. 2010;50:81–98.

[7] Smith S.M., Miller K.L., Salimi-Khorshidi G., et al. Network modelling methods for fMRI. NeuroImage. 2011;54:875–891.