Time correlation of EPI versus real-time fMRI time series

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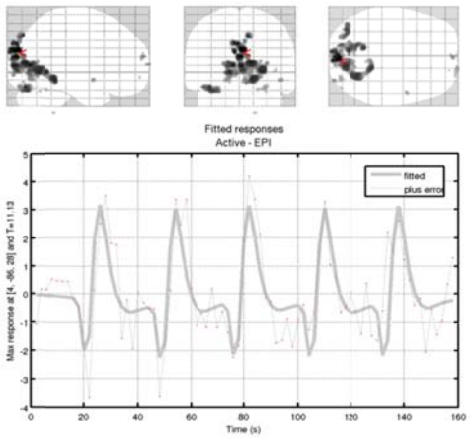

Fig. 1 - EPI adjusted time course of activation (bottom) and orthogonal views of the brain (top), threshold 5.55 (p<0.05, FWE).

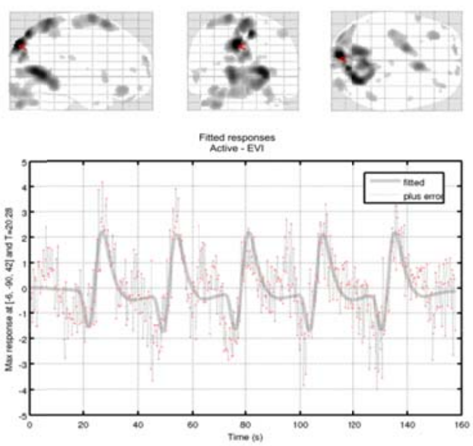

Fig. 2 - EVI adjusted time course of activation (bottom) and orthogonal view of the brain (top), threshold 5.02 (p<0.05, FWE).

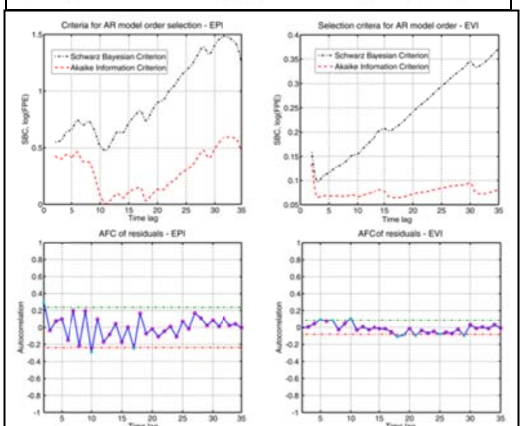

Fig. 3 - SBC and AIC model order selection criteria (top) and uncorrelatedness of residuals (bottom) for fMRI EPI time series (left) and EVI time series (right).

Target audience

The study is of potential interest for the MRI community interested in optimally processing real-time fMRI data by refining the hypothesis-driven statistical analysis.

Purpose

Analysis of real-time fMRI signals is subject to temporal dispersion of the hemodynamic response and aliasing of physiological noise. Echo-volumar imaging (EVI) [1][2], inverse imaging (InI) [3], highly undersampled projection imaging (PI) [4], and compressed sensing (CS) MR image reconstruction [5] enable temporal resolution down to 100 ms. Extremely short acquisition (TR) poses the problem of serial correlations among voxels studied here in the context of autoregressive (AR) models.

Methods

An AR(p) model is a stochastic process described by a weighted sum of its previous values and white noise error. As the model order p increases the estimates are more accurate. The RMS plot of the difference between the AR(p) estimated series and the actual series typically decreases rapidly down to a plateau; an appropriate order is the next point after flattening.

The time series of residuals and the significance level were computed by a modified Li-McLeod portmanteau test [6]. Residual analysis consisted of the whiteness test (autocorrelation of residuals within a confidence interval) and the independence test (uncorrelatedness of residuals with past inputs).

Results and Discussion

Full brain fMRI data were analyzed in terms of BOLD contrast in a finger-tapping multi-subject multi-session task. Both fast spin echo EPI and multi-slab EVI data acquisitions were carried out at 3 T, following the same paradigm run by all participants. EPI consisted of 84 scans at TR=2 s, 32 slices, acquisition matrix 64x64, voxel size 2x2x2, and the first 5 volumes discarded. EVI consisted of 600 scans at TR=0.280 s, 32 slices, acquisition matrix 64x64, voxel size 4x4x4, and the first 36 volumes discarded. AR models were fitted for both EPI and EVI data (Fig.1 & Fig.2) by adapting the ARfit algorithm [7] that estimates the Schwarz's Bayesian criterion (SBC)[8] and the logarithm of Akaike's final prediction error (FPE)[9] leading to the smallest stepwise mean-squared prediction error for model order selection criteria. Likewise, approximate confidence intervals for the estimated parameters and statistics to assess the adequacy of a fitted model were computed.

The experiments concluded with p=11 for EPI and p=17 for EVI time series. The difference was found statistically significant by Krusker-Wallis non-parametric statistic test on 5 subjects running multiple identical EPI and EVI sessions. Parameters not statistically significant were discarded and the adequacy of representation was evaluated by the uncorrelatedness of residuals (Fig.3), which enabled computing of confidence intervals for significant AR parameters. Residual analysis plots show different information depending on time-domain or frequency-domain input-output validation data used.

Conclusion

AR modeling may contribute to better understanding of physical systems by revealing processes responsible of persistence into the time series. Dynamical characteristics of complex systems can be inferred from analyses of stochastic time series models fitted to experimental data and decomposition into eigenmodes and associated oscillation periods, damping times, and excitations. The high order of fitted AR models for fMRI data suggests that correction of serial correlations is crucial in inferential statistical analysis.

Since each voxel is represented as a time series of neurophysiological activity summing up the cognitive and sensorimotor conditioning that underlies the BOLD response, a multivariate AR model (MAR) is more realistic. MAR models are fully connected and fitting them to data generates sub-networks that may explain the observed brain dynamics.

References

1. Rabrait C, Ciuciu P *et al.* (2008), *J Magn Reson Imaging* 27(4):744-53. **2.** Posse S *et al*. (2012) *Neuroimage 61***:**115-130 **3.** Lin FH, Witzel T *et al.* (2010), *Neuroimage* 49(4):3086-98. **4.** Grotz T, Zahneisen B, *et al.* (2009), *Magn Reson Med 62*(2):394-405. **5.** Lustig M *et al***.** (2008) *IEEE Signal Processing Magazine*,75-82. **6.** Li W, McLeod A (1981), *J. Roy. Statist. Soc. Ser. B*, 43:231–239 **7.** Neumaier A, Schneider T (2001), *ACM Trans Math Software* 27(1):27-57. **8.** Schwarz(1978), *Ann Statist* 6:461-64. **9.** Akaike (1974), *IEEE Trans Autom Control* **19**(6):716-23.

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