The impact of physiological noise correction on fMRI at 7T

C. Hutton[1], O. Josephs[1], J. Stadler[2], E. Featherstone[1], A. Reid[1], O. Speck[3], J. Bernarding[4], and N. Weiskopf[1]

[1]Wellcome Trust Centre for Neuroimaging, Institute of Neurology, University College London, London, United Kingdom, [2]Special Lab Non-Invasive Brain Imaging, Leibniz Institute for Neurobiology, Magdeburg, Germany, [3]Department of Biomedical Magnetic Resonance, Institute for Experimental Physics, Otto-von-Guericke University, Magdeburg, Germany, [4]Institute for Biometry and Medical Informatics, Faculty of Medicine, Otto-von-Guericke University, Magdeburg, Germany

Introduction

Motivation: In BOLD fMRI studies, the signal-to-noise ratio of the time-series (tSNR) can be an indication of how well brain activations will be detected. The non-neuronal noise sources contributing to tSNR can be considered as physiological (e.g. from subject cardio-respiratory effects and movement), and non-physiological or thermal (e.g. from the scanner hardware). As image SNR increases, the relative contribution of physiological noise to the total tSNR will be greater compared with that from thermal noise [1]. Consequently strategies for reducing the effects of physiological noise on tSNR are extremely important for fMRI studies at ultra high fields.

Background: Methods have been proposed to model and correct for physiological fluctuations in fMRI time-series [2-5]. Recent studies have exploited these methods to demonstrate an improvement in delineation of activity in the presence of task correlated physiological noise [6] and to investigate the relative contribution of physiological noise components to the observed fMRI signal at 7T [7].

Aims: In this study, we aim to demonstrate the impact of physiological noise correction on the detection of brain activations for BOLD fMRI studies acquired at 7T. The higher SNR available at 7T can be exploited to acquire high resolution data (e.g. [8]). In contrast in this study we use a lower image resolution (3x3x2mm^3) similar to that typically used for cognitive neuroimaging studies at 3T to acquire fast whole brain images with higher SNR. Using fMRI studies of subjects at rest and performing a visual task we investigate the impact of physiological noise correction on tSNR as a function of image SNR and on the t-scores associated with detected activations.

Methods

Data acquisition: Five subjects were scanned on a 7T whole body MR-system (Siemens, Erlangen, Germany) using a 24-channel receive head coil with dedicated CP coil for RF transmission (Nova Medical,Inc.,Wilmington MA). 5 runs of 150 EPI volumes were acquired with different flip angles (8º, 16º, 26º, 38º and 70º (=Ernst angle)) to manipulate the image SNR and time-series SNR while the subject was at rest with eyes open. 20 EPI volumes were acquired with no RF excitation to provide a thermal noise measurement [9]. During an additional EPI run acquired with flip angle=70º, the subject was visually presented with 20s of flashing black/white hemi-field wedges alternating between left and right field of view, interspersed with 20s of a blank screen (stimulus cycle=80s repeated 5 times). EPI acquisition parameters were matrix=64x64, in-plane resolution=3x3mm^2, slices=40, slice thickness=2mm+1mm gap, TE=25ms, volume TR=2s, echo-spacing=500µs, BW=2298Hz/Px. The slice orientation and positioning for the EPI volume was transverse oblique in alignment with and centered on the calcarine fissure. Throughout all of the experiments the subjects' cardiac and respiratory states were recorded using a pulse oximeter and pneumatic belt respectively with a sampling rate of 100 Hz. A gradient echo field map and a T1-weighted anatomical image (MPRAGE, resolution=1mm^3) were also acquired for each subject.

Data processing and analysis: EPI data were processed using SPM8 [10] and routines implemented in MATLAB (2009a, The MathWorks, Natick, MA) in the following way. The effects of head motion, geometric distortion and the interaction between the two were reduced using the FieldMap toolbox together with Realign and Unwarp in SPM8 [11,12]. Low frequency drifts were modeled using a linear and quadratic function of image number. Signal fluctuations arising from cardiac and respiratory activity were modeled using a method based on RETRIOCOR [3] and sampled at a reference slice within the visual cortex [4]. The time-series acquired with varying flip angles were corrected for the different fluctuations using a General Linear Model (GLM). Thermal noise was calculated from the standard deviation of the images acquired without RF excitation corrected for the Rician distribution and the number of coils [13]. The mean image SNR (SNR0) and tSNR within an ROI defined in the visual cortex was calculated for each time series after correcting for the different fluctuations and averaged over subjects. SNR0=time-series mean divided by thermal noise; tSNR=time-series mean divided by its standard deviation [9]. TSNR as a function of SNR0 for each correction method was fitted to the model proposed in [1] to estimate the value λ relating the point (1/λ) at which tSNR is degraded by signal-dependent fluctuations. For the visual fMRI time-series, 4 different GLMs were constructed, each comprising regressors representing the visual stimulus A) alone, or with B) cardiac effects, C) respiratory effects or D) both. The GLMs were fitted after high-pass filtering the time-series and voxel-wise t-tests were performed to detect BOLD activation effects. The average voxel-wise improvement in t-score for models B, C and D compared with A was calculated for voxels in the ROI with t-score>3.14 (p<0.001).

Results

Figure 1a

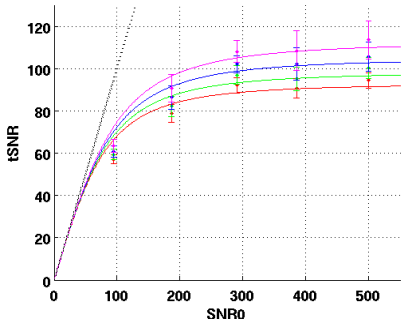

Figure 1b

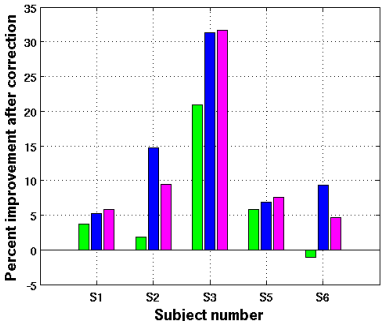

Fig. 1a. tSNR vs SNR0. Each point represents the average tSNR over visual cortex ROI for flip angle=8º,16º,26º,38º and 70º (from the left) ± standard error over 5 subjects. Different lines correspond to the fit of the model in [1] to the time-series after correction for different effects; low frequency (red), low frequency and cardiac (green), low frequency and respiratory (blue), low frequency, cardiac and respiratory (pink). The respective model fits resulted in 1/λ = 92.6, 98.1, 105.3, 112.4.

Fig. 1b. Percent improvement in t-scores averaged over visual cortex ROI for each subject, for models B (green), C (blue) and D (pink) compared with A.

Discussion

The results demonstrate that correcting for physiological fluctuations leads to an increase in tSNR in visual cortex from approximately 10% at lower flip angles up to 20% for the highest flip angle. Correcting for respiratory effects alone has a greater impact on tSNR than correcting for cardiac effects. The results of fitting the model from [1] to the time-series before applying any corrections for physiological fluctuations resulted in values for 1/λ which were in agreement with the literature [1,9]. After applying corrections, 1/λ also increased by approximately 20%. Similar results were found when other grey matter regions of the brain were investigated. However, the increase in tSNR relative to the maximum available SNR is still limited (i.e. 110:500). This additional noise may be explained by low frequency physiological fluctuations (e.g. [2,15]) which will be further investigated. It may also be due to other effects such as spontaneous neuronal fluctuations. The results of the visual fMRI study showed that the physiological noise correction lead to voxel-wise improvements in t-scores of between 5 and 30%. The impact of different corrections on fMRI statistics was variable across subjects further highlighting the spatial and temporal variability of physiological fluctuations. It has been shown that by increasing EPI image resolution at 7T, the corresponding reduction in SNR beneficially leads to a reduction in the relative contribution of physiological noise to tSNR [9]. Here we have demonstrated that physiological noise correction methods can increase tSNR for EPI acquired at a lower resolution and without sacrificing image SNR.

References

1) Kruger and Glover, 2001, MRM; 2) Birn et al., 2006, Neuroimage; 3) Glover et al., 2000, MRM; 4) Josephs et al., 1997, ISMRM; 5) Lund et al., 2006, Neuroimage; 6) Birn et al., 2009, Neuorimage; 7) Bianciardi et al., 2009, MRI; 8) Speck et al., 2008, MAGMA; 9) Triantafyllou et al., 2005, Neuroimage; 10) Friston, 2007, Statistical Parametric Mapping; 11) Andersson et al., 2001, Neuroimage; 12) Hutton et al., 2004, ISMRM; 13) Constantinides et al., 1997, MRM; 15) Shmueli et al., 2007, Neuroimage.

Acknowledgements: Funded by the Wellcome Trust[1], Center for Behavioral Brain Sciences, Magdeburg[2], DFG-grant SP 632/3-1[3].