Characterization and Reduction of Cardiac- and Respiratory- Induced Noise as a Function of the Sampling Rate (TR) in fMRI

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Target audience

This study is important in fMRI resting-state data analysis to correct the influence of low-frequency and high-frequency physiological noise.

Purpose

The purpose of this study is to estimate both low-frequency and high-frequency physiological noise regressors and investigate the aliasing property of the high-frequency cardiac waveform as a function of the sampling rate (TR). In particular, we would like to answer the following questions: How can smoothly-varying low-frequency physiological noise regressors be derived using a penalization method and cross-validation? Is the probability density function of the signal associated with the high-frequency cardiac wave stationary for resting-state data? If so, do favorable subject-specific TRs exist where the aliasing property of the cardiac pulsations are predictable and do not overlap into the low-frequency BOLD range? How much of the physiological noise can be eliminated? To answer these questions, we performed a detailed analysis of the physiological noise sources and computed the aliasing properties of cardiac and respiratory noise at different sampling rates. Results were compared with a recent study[1].

Methods

Imaging: Six normal subjects with previous fMRI experience (mean age 23) were scanned. Subjects were instructed to rest, keep eyes closed and be as motionless as possible. FMRI was performed in a 3.0 T Trio Tim Siemens MRI scanner (12-channel head coil, GRAPPA=2, 32 reference lines, TE=25ms, FOV=22 cm×22 cm, 14 slices in oblique axial direction covering prefrontal cortex, brainstem and cerebellum, thickness/gap=3.0 mm/1.0 mm, resolution 64×64, BW=2170Hz/pixel, 180 time frames. For each subject 20 different data sets corresponding to 20 different TRs (700ms, 800ms, …, 2600ms) were collected. During EPI heart rate and respiratory rate were recorded using a pulse-oximeter and respiratory belt, respectively (sampling rate 50Hz).

Analysis: High-frequency physiological regressors are computed from the externally recorded heart rate and respiratory rate using intensity normalization and time-shifting where for each voxel the optimal shift is determined from the fMRI data using maximum correlation. To determine subject-specific low-frequency physiological response functions $h_C(t)$ and $h_R(t)$, we use an optimization technique with cross-validation. These physiological regressors are formed by $X_C(t)=C_{LF}(t)*h_C(t)$ and $X_R(t)=R_{LF}(t)*h_R(t)$ where $C_{LF}(t)$ is a function that desribes the change of the cardiac rate as a function of time and $R_{LF}(t)$ is a measure of the change of the respiratory volume per unit time. The new approach in obtaining the corresponding impulse response functions $h_C(t)$ and $h_R(t)$ is by using a family of established response functions[1], adding orthogonal terms to make the response functions more general, adding a constraint that insures smoothness of the curvature (second derivative) of these functions, and finally determining the optimum curvature and all other unknown parameters by cross-validation. In particular, for the cardiac response function we use $h_C(t)= h^{(0)}{}_C(t)+\alpha\ d/dt\ \ h^{(0)}{}_C(t)$, where $h^{(0)}{}_C(t)$ is a sum of a Gamma function and a Gaussian function with unknown parameters $\{a_1,\ldots,a_6\}$ and α *is* an additional parameter to allow flexibility. Normalization of $h_C(t)$ eliminates one unknown parameter resulting in 6 free parameters that we collectively call $x=\{a_2,\ldots,a_6,\ \alpha\}$. To determine all unknown parameters, we use a 2-step approach with cross-validation. For each voxel of data set 1, we compute the squared residual error $\eta(x)=(y-Xb)'(y-Xb)$ according to the general linear model $y=Xb+\varepsilon$ where y is the voxel time series, X the design matrix containing the physiological regressors with unknown values of the parameters x, and ε the residual. We then solve the optimization problem

$$x_{\lambda\mu} = \arg\min\ (<\eta(x)> +\lambda \mid \int_0^{30s} \mid \frac{d^2}{dt^2} h_C(t) \mid dt - \mu \mid)$$

where we explicitly include regularization parameters {λ, μ} to penalize the mean curvature of the physiological response function using the L1 norm. The optimum set of parameters $x_{\lambda,\mu}$ is determined by cross-validation using a second data set. A similar procedure is used for determining the optimized parameters for the respiratory response function, based on a family of two Gamma functions plus derivative.

Results

In Fig.1, the subject-optimized cardiac and respiratory response functions are shown, respectively, for all 6 subjects. For a typical subject we show in Fig.2 the regions in the brain that are mostly affected by the physiological noise sources (high-frequency cardiac activity (1. row), high-frequency respiratory activity (2. row), low-frequency cardiac activity (3. row), and low-frequency respiratory activity (4.row)). In Fig.3 we have calculated the probability that the cardiac frequency aliases to a frequency range above 0.1 Hz and therefore does not overlap with the low frequency BOLD signal.

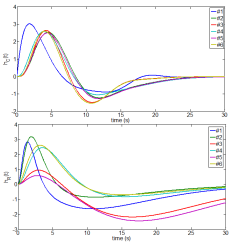

Fig.1 Subject-optimized cardiac and respiratory response functions

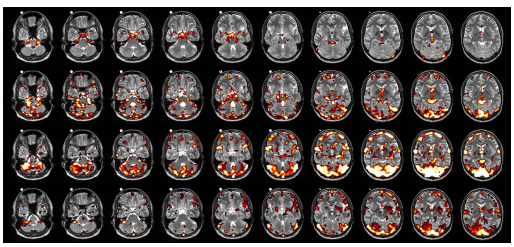

Fig.2 High-freq. (HF) and low-freq. (LF) cardiac and respiratory noise (p<0.05) top to bottom: HF cardiac, HF respiratory, LF cardiac, LF respiratory

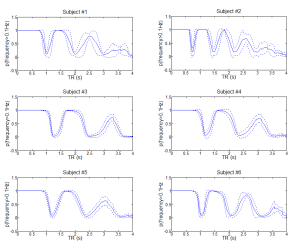

Fig.3. High-frequency (f>0.1Hz) cardiac content as a function of TR (p<0.05)

Discussion

A particular focus of this research was to investigate if a subject-optimized TR can be chosen where the high-frequency cardiac rate does not alias into the low-frequency BOLD range. This is indeed the case, as we have shown by computing the temporal SNR as a function of TR. Since the cardiac high-frequency activity was very stable for each subject during a 2h of scanning time, it is possible to predict where the cardiac frequency will alias to. Thus, by knowing the mean cardiac frequency and its standard deviation for each subject (for example from pilot studies), it is possible to choose an optimal TR to reduce aliasing of the high-frequency cardiac noise into the low-frequency BOLD range. This approach could have advantages for mapping activations of the brainstem or nearby spinal cord regions, which are inherently difficult to study with fMRI because of the large vibrations associated with the heartbeat. According to our calculations, the temporal SNR can be improved by about 40-50 in problem areas if an optimal TR is chosen. However, for the majority of grey matter voxels in the upper cortex, high-frequency cardiac noise is relatively absent.

Conclusion

In summary, modeling of all four physiological noise sources can lead to significant improvements in fMRI resting-state data quality. The high-frequency cardiac noise is mostly associated with the brainstem, nearby spinal cord and larger blood vessels. The cardiac noise affecting the brainstem and other nearby regions can be efficiently eliminated for fMRI using imaging at subject-specific TRs where the high-frequency cardiac noise will not alias into the BOLD frequency range.

References

[1] Chang, C., Cunningham, J.P., Glover, G.H. 2009. Influence of heart rate on the BOLD signal: The cardiac response function. *NeuroImage* 44:857-869.