REGRESSOR SELECTION FOR RETROICOR AND RETROKCOR CORRECTIONS OF 3D FMRI DATA

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Introduction Segmented 3D readouts allow high-resolution low-distortion functional imaging, but are prone to physiological signal fluctuations in areas like the brainstem. In the current work **we explore the use of retrospective corrections, in order to remove temporal instabilities from 3D FMRI acquisitions**. Retrospective corrections can either be employed in image space (RETROICOR [1]) or k-space (RETROKCOR [2]). A previously proposed method by our group uses **the Bayesian Information Criterion (BIC) to determine an optimal subset** of RETROICOR regressors with the aim to maximize the degrees of freedom (DOF) of the statistics [3]. It was shown that the optimal set of regressors varies from one voxel to another, but we also expect that it will be influenced by the acquisition method (e.g., contrast mechanism and readout). We therefore consider 2D GRE-EPI, 3D balanced SSFP (bSSFP) and spoiled gradient echo (SPGR) data, acquired with and without a real-time cardiac synchronized readout that aims to reduce cardiac fluctuations prospectively [4], to see which regressors are meaningful for each acquisition method. Optimizing the correction voxelwise using various regression models depending on the spatial location is non-trivial when using RETROKCOR. We therefore choose to use one model, which is optimal for our region of interest, the brainstem. **The results suggest that the optimal number of regressors is highly dependent on the acquisition and can even be zero (i.e., no retrospective correction) in some cases.**

Theory The Bayesian Information Criterion (BIC) is defined as: $BIC(k) = N\ln(RSS(k)/N)+k\ln(N)$, where N is the number of samples, k is the number of regressors, and $RSS(k)$ is the residual sum of squares. The BIC is used to compare models with a different number of regressors, with low BIC indicating the preferred model. Models that explain a large portion of the variance (having low RSS) are favored, but a large number of regressors is penalized to prevent over-fitting the data. In our approach, the optimal set of regressors is determined by iteratively expanding the set with a new regressor as long as $BIC(k+1)<BIC(k)$. In the original method [4] the next candidate regressor is determined after each iteration by calculating which of the remaining regressors explains the greatest amount of the remaining variance. For RETROKCOR, however, this is computationally too demanding as the regressions are performed on the pre-combined multi-channel data. Instead, we determine the order of the candidate regressors beforehand based on the variance reduction in the brainstem based on the regression with each of the regressors individually. The two approaches are equivalent if the regressors are independent (i.e., non-correlated).

Methods 3D bSSFP and SPGR data were acquired in four healthy volunteers on a 3T Siemens TIM TRIO system using a 12-channel head coil. SPGR and bSSFP data were acquired with the following parameters: α=30°, TR/TE=12/6, FOV=192x192x48 mm, Matrix=96x96x24, BW=1860 Hz/pix, 8 lines per TR, Tvol = 3.5 s, 60 volumes using a 3D stack-of-segmented EPI readout [5]. Additionally, multi-slice GRE-EPI data were acquired: α=90°, TR=3500, TE=30 ms, FOV=192x192x48 mm, Matrix=96x96x24, BW=1860 Hz/pix, 8 lines per TR, 60 volumes. The cardiac and respiratory waveforms were recorded using a plethysmograph and pneumatic bellows to create a set of 18 regressors based on the cardiac and respiratory phase; three orders of Fourier series for the cardiac terms, four orders for the respiratory terms, and first-order interactions [6]. Four additional regressors, based on cardiac and respiratory rate [7,8] and their temporal derivatives, were included to allow for temporal shifts. Table 1 lists all the regressors tested.

Table 1: List of regressors tested.

No.	Description	No.	Description
1	cardiac: First order cosine	12	Respiratory: Third order sine
2	cardiac: First order sine	13	Respiratory: Fourth order cosine
3	cardiac: Second order cosine	14	Respiratory: Fourth order sine
4	cardiac: Second order sine	15	Interaction: (card + resp) cosine
5	cardiac: Third order cosine	16	Interaction: (card – resp) cosine
6	cardiac: Third order sine	17	Interaction: (card + resp) sine
7	Respiratory: First order cosine	18	Interaction: (card – resp) sine
8	Respiratory: First order sine	19	Cardiac rate
9	Respiratory: Second order cosine	20	Cardiac rate derivative
10	Respiratory: Second order sine	21	Respiratory rate
11	Respiratory: Third order cosine	22	Respiratory rate derivative

Results The top row in Fig. 1 shows the fraction of the signal variance in the brainstem that remains after regression with each of the individual regressors listed in Table 1. Results are shown for 2D GRE-EPI (RETROICOR), and 3D bSSFP (with and without cardiac synchronization, both RETROKCOR). The dotted line represents the variance reduction expected from a randomly constructed regressor. It is striking that the majority of the respiratory regressors do not explain more than a randomly constructed regressor in all three sequences. For 2D GRE-EPI, only the first order cardiac terms (#1—#2) appear to explain real physiological fluctuations, whereas for non-synchronized bSSFP the cardiac regressors up to the third order (#1--#6) explain a significant amount of variance. For synchronized bSSFP the cardiac regressors explain very little variance. Figs 1(d—f) show the variance reduction with each model expansion step. The corresponding BIC values are shown in (g—i). The red arrow denotes the optimal model. For non-synchronized bSSFP six regressors are selected. These regressors together explain 0.67±0.03 of the variance (e). Fig. 2(a) shows the ROI that was used to determine the optimal regressor set and the variance reduction map obtained with the optimal model (b). No regressors, however, are selected for non-synchronized bSSFP as the cardiac fluctuations are corrected prospectively by the readout. After retrospective correction the temporal SNR (tSNR) for non-synchronized bSSFP is increased from 14±1 to 17±1. The tSNR of synchronized bSSFP was found to be 19±0.5, indicating that retrospective corrections could potentially provide an alternative to mitigate cardiac fluctuations when a prospective correction method is unavailable, as long as the regressors are picked appropriately in order to prevent overfitting of the data.

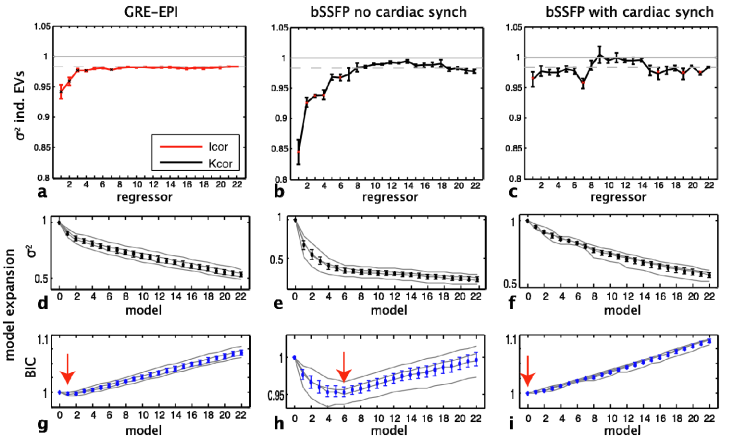

Figure 1: The residual variance in the brainstem (normalized to non-corrected data) after regression with each of the regressors individually (a—c). Based on a—c the regressors are sorted and added iteratively to determine the optimal model. The residual variance after each model expansion step is shown in (d—f), and the corresponding BIC in (h—i). The red arrow marks the minimum BIC for each sequence.

Discussion and Conclusion We have shown that **the optimal set of nuisance regressors is highly dependent on the pulse sequence and the readout** that is used for the acquisition. Although it is advisable to consider all potential regressors, including all possible regressors will result in significant reduction of the degrees of freedom (DOF) in the functional analysis. **The BIC selection procedure was adapted and applied to RETROKCOR corrections of 3D data for which it successfully selected only meaningful regressors** depending on whether signal fluctuations were mitigated prospectively or not (cardiac synchronized vs. non-synchronized data).

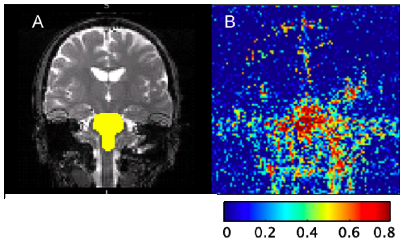

Fig 2: Non-synchronized bSSFP showing (a) the brainstem and (b) the obtained variance reduction when the optimal model is used.

References. [1] Glover, MRM, 2000. [2] Hu, MRI, 1995. [3] Jenkinson, Proc. ISMRM, 2009. [4] Tijssen et al. NIMG 2011. [5] Miller et al. MRM 2006. [6] Brooks, NIMG, 2008. [7] Birn. NIMG, 2006 [8] Shmueli. NIMG, 2007.