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Incorporating hemodynamic response functions to improve analysis models for sparse-acquisition experiments

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Introduction: Prior fMRI studies utilizing sparse imaging have primarily used a finite impulse response model for statistical analysis, effectively treating each experimental trial as independent. In such studies, it is typical to collect one or more image volumes after a delay following the onset of stimulus presentation and/or participant response. This leverages on the fact that the peak of hemodynamic response to an impulse like event is reached approximately 6s after the event. However, what is often ignored is that the tail of the response may last as long as another 30s. Furthermore, many of these studies use an inter-stimulus interval (ISI) less than 10s. Thus, it is very likely that the observed BOLD response following an event will be influenced by the BOLD responses to at least the prior event. We present a method for analysis of such sparse-imaging data by incorporating a hemodynamic response function in the model.

Methods: For each condition of interest in the study, we create a time series representing the onsets of each event of interest. In the likely scenario that such events are not impulse like, we convolve each event with a boxcar whose length corresponds to the duration of that specific event. The resulting time series is then convolved with a canonical hemodynamic response function in order to generate a simulated BOLD response for that condition. This BOLD response is then sampled (without any low-pass filtering) at the time-points where the data were actually acquired. By not low-pass filtering the data, we introduce similar aliasing artifacts as would be observed in the actual fMRI data acquisition. The sampled vector is then used as a regressor in the general linear model analysis. Such regressors are created for each condition of interest. We ran computer simulations using these regressors and their derivatives to estimate decreases in residuals of fitting the two different models to synthetic data (Figure 1). We also used this approach to analyze an fMRI study in which 15 adult English speakers completed a grammaticality judgment task with task (ungrammatical) and control (grammatical) sentences.

Results: The results of comparing the task and control conditions are shown in Figure 2. The left panel shows the result from using the common FIR approach while the right panel shows the result from using the approach described above. Improved statistical significance is observed for the analysis incorporating the HRF-based regressors: FIR approach (left) allows us to observe significant left IFG activations only at $p < 0.01$ (uncorrected), while the proposed approach (right) allows us to observe significant left IFG activations at $p < 0.001$ (corrected).

Conclusions: The simulations suggest that the decreased residual error can be obtained by generating a model via sparse-sampling of HRF-based regressors and their derivatives. As expected, addition of HRF-based regressors in analysis increases the model’s accuracy, decreases the error and therefore increases the statistical significance in the fMRI study. The results are of particular importance for sparse designs that strive to reduce the duration of silent periods, as for instance in pediatric imaging.

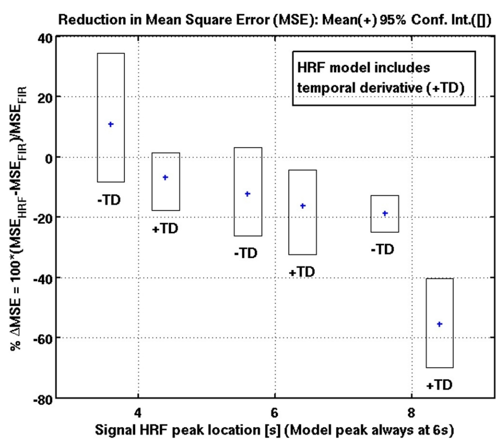

Figure 1. Percentage reduction in Mean Square Error from fitting HRF-based and FIR models to synthetic data at 5dB signal-to-noise ratio. +TD: temporal derivative was sampled for the HRF-based model.

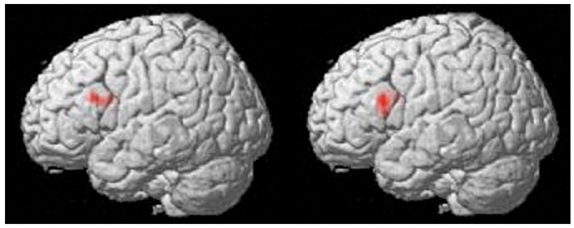

Figure 2. Statistical results comparing grammaticality judgments in 15 adults. Left panel: FIR approach yielded significant left IFG activation at $p < 0.01$ (uncorrected). Right panel: HRF-based regressors yielded significant left IFG activation at $p < 0.001$ (corrected)