A Comparison of Parametric and Non-Parametric Blind Hemodynamic Deconvolution Methods for fMRI

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Introduction: Functional MRI (fMRI) is a Blood Oxidation Level Dependent (BOLD) technique which does not directly measure neuronal activity [1]. The measured fMRI signal is assumed to be the linear convolution of latent neuronal response and the Hemodynamic Response Function (HRF). The main interest in any fMRI study would be to study the latent neuronal response and since the sources of HRF variability can be non-neuronal in nature [2], it is advantageous to deconvolve the HRF from the fMRI signal. This has many applications, especially in the emerging field of causal connectivity analysis [3]. Existing approaches have employed parametric methods such as Cubature Kalman filter [4] and dynamic expectation maximization [5], wherein the parameters of an expanded biophysical model of the BOLD response are estimated in order to recover the unknown HRF and latent neuronal variables. Even though these models, especially the Kalman filter based approach, seem to give excellent results [4], it is unclear whether these highly parameterized models have an over fitting problem. To investigate this aspect, we present a method which uses non-parametric blind deconvolution based on homomorphic filtering and compare it with the performance of cubature Kalman filter-based approach.

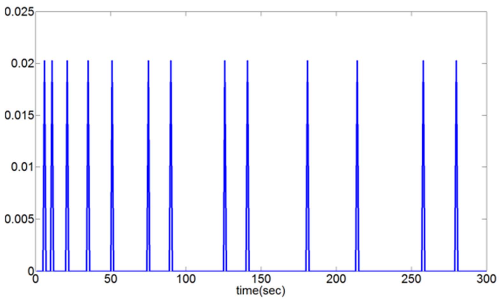

Fig.1 *Simulated input*

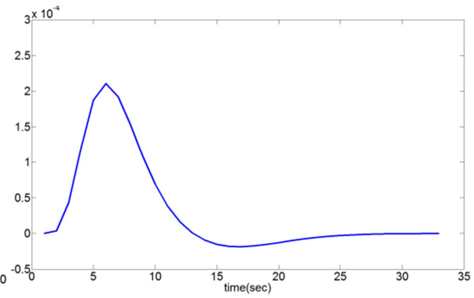

Fig.2 *Simulated HRF*

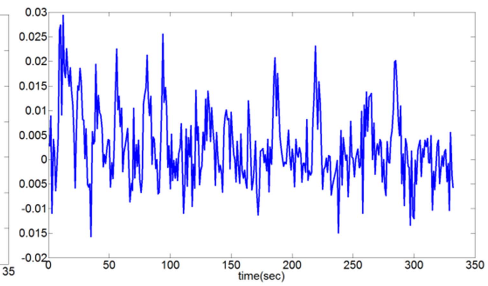

Fig.3 *Hypothetical fMRI signal*

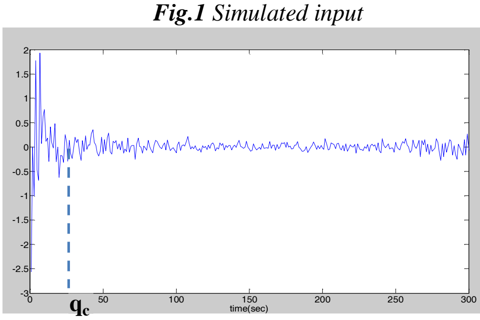

Fig.4*: Cepstral domain representation of simulated fMRI signal*

Methods: A sequence of impulses of equal amplitude convolved with a Gaussian like function was generated as the hypothetical input (Fig.1). This hypothetical input was then convolved with a canonical HRF obtained from SPM (Fig.2). The resultant signal was down-sampled to mimic a TR of 1sec, and noise with SNR=2db was added to obtain the simulated fMRI signal (Fig.3). The cepstral domain [6,7] representation of the simulated fMRI signal (Fig.4), $c_x(n)$, was obtained.

$$c_x(n) = \frac{1}{2\pi}\int_{-\pi}^{\pi} \log[X(e^{j\omega})]\, e^{j\omega}\, d\omega$$

where $X(e^{jw})$ is the Fourier transform of the simulated fMRI signal. Since the HRF and neuronal responses are low and high frequency signals respectively, a separation is visible in the cepstrum (shown in Fig.4). Subsequent liftering [8] at a particular cutoff quefrency (q_c) gave us the latent neuronal response. To obtain the approximate threshold quefrency, a grid search was performed. An additional factor considered was the length of the FFT; it was varied 0.01 times the length of the input so that we can get good cepstral resolution. The above process is called homomorphic deconvolution. For comparison, hemodynamic deconvolution of the simulated fMRI data was also performed using the cubature Kalman filter based approach.

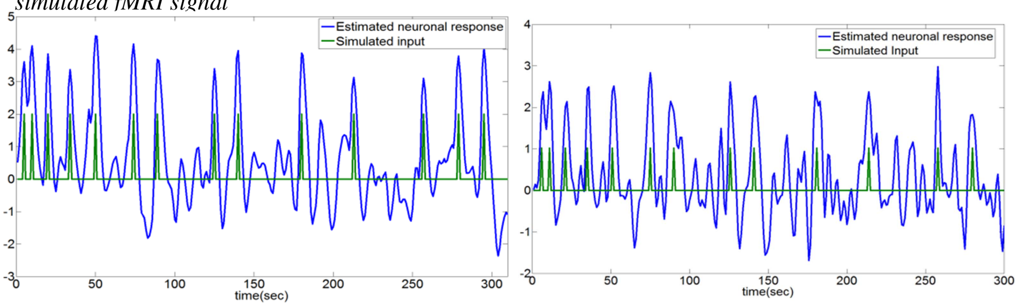

Fig.5*: Plot showing the simulated input and estimated neuronal response obtained by using parametric blind deconvolution (left) and homomorphic deconvolution (right)*

Results and Discussions: Fig.5 shows the comparison between the performance of the homomorphic and cubature Kalman filter based deconvolutions. The correlation between simulated and estimated neuronal inputs was 0.4524 and 0.4624 for homomorphic and Kalman methods, respectively ($p<0.05$ for both). Importantly, Fig.5 shows that in both cases, the temporal neuronal events were correctly estimated. Since the homomorphic method is non-parametric and does not make any assumptions, these results confirm that parametric methods such as cubature Kalman filter-based approaches make valid assumptions and are not susceptible to over fitting.

References: **[1]** Buxton, *Neuroimage*, 23, S220–S233, 2004.**[2]** Handwerker *et al, NeuroImage*, 21, 1639-1651, 2004. **[3]** Deshpande, *et al, Brain Connectivity*, 2(5), 235-245, 2012. **[4]** Havlicek, *et al*, *NeuroImage,* 56(4): 2109-2128, 2011. **[5]** Friston *et al*, *NeuroImage*, 41(3):849-85, 2008. **[6]** Oppenheim *et al*, *IEEE Signal Processing Magazine*, 21: 95-106, 2004. **[7]** Bogert, *et al***,** *Proc. of the Symosium. on Time Series Analysis,* pp 209-243, 1963. **[8]** Oppenheim *et al*, Proc. IEEE, Vol. 56, pp. 1264-1291, 1968.