

Does the requirement of convolving a time series with the hemodynamic response function underlie a frequency dependence?

Thomas A. Dorfer ^{1,2}, James A. Roberts ¹, Michael Breakspear ^{1,3}, Leonardo L. Gollo ^{1,2}

¹ Systems Neuroscience Group, Queensland Institute for Medical Research, Brisbane, Australia

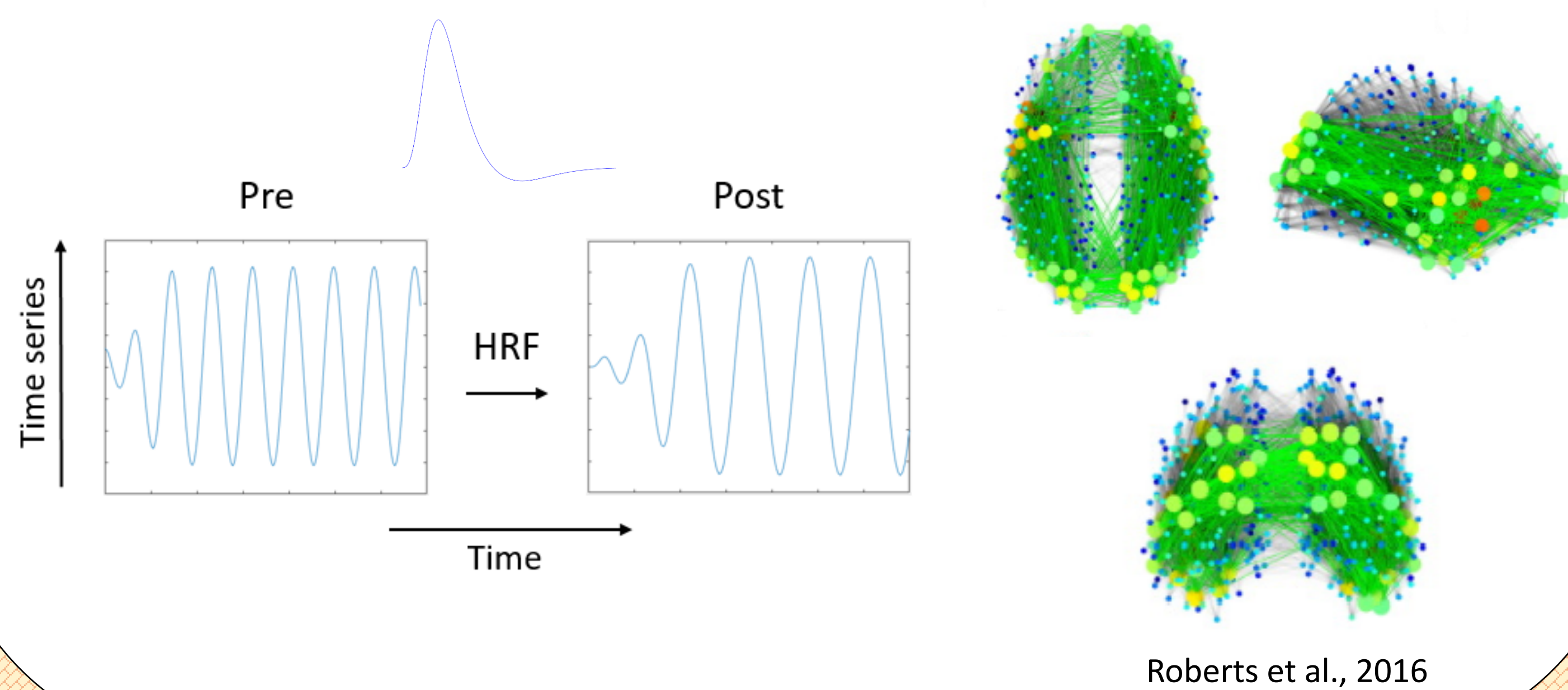
² Faculty of Medicine, University of Queensland, Brisbane, Australia

³ Metro North Mental Health Service, Herston, Queensland, Australia



Introduction

Computational models of brain activity enable multimodal experimental data to be incorporated into a framework that facilitates the simulation of both ordinary and pathological behaviors (Breakspear, 2017). This effort particularly benefits from modern neuroimaging techniques such as blood-oxygen-level-dependent (BOLD) functional magnetic resonance imaging (fMRI). Convolution of the regional stimulus-evoked BOLD response, also known as the hemodynamic response function (HRF), is a linear approximation to simulate hemodynamics and a technique frequently used in studies aiming to model brain function (Friston et al., 2000; Buxton et al., 2004; Lindquist et al., 2009). Due to its slow time scale (seconds), however, the HRF acts as a low-pass filter and therefore behaves differently for fast and slow signals.



Materials & Methods

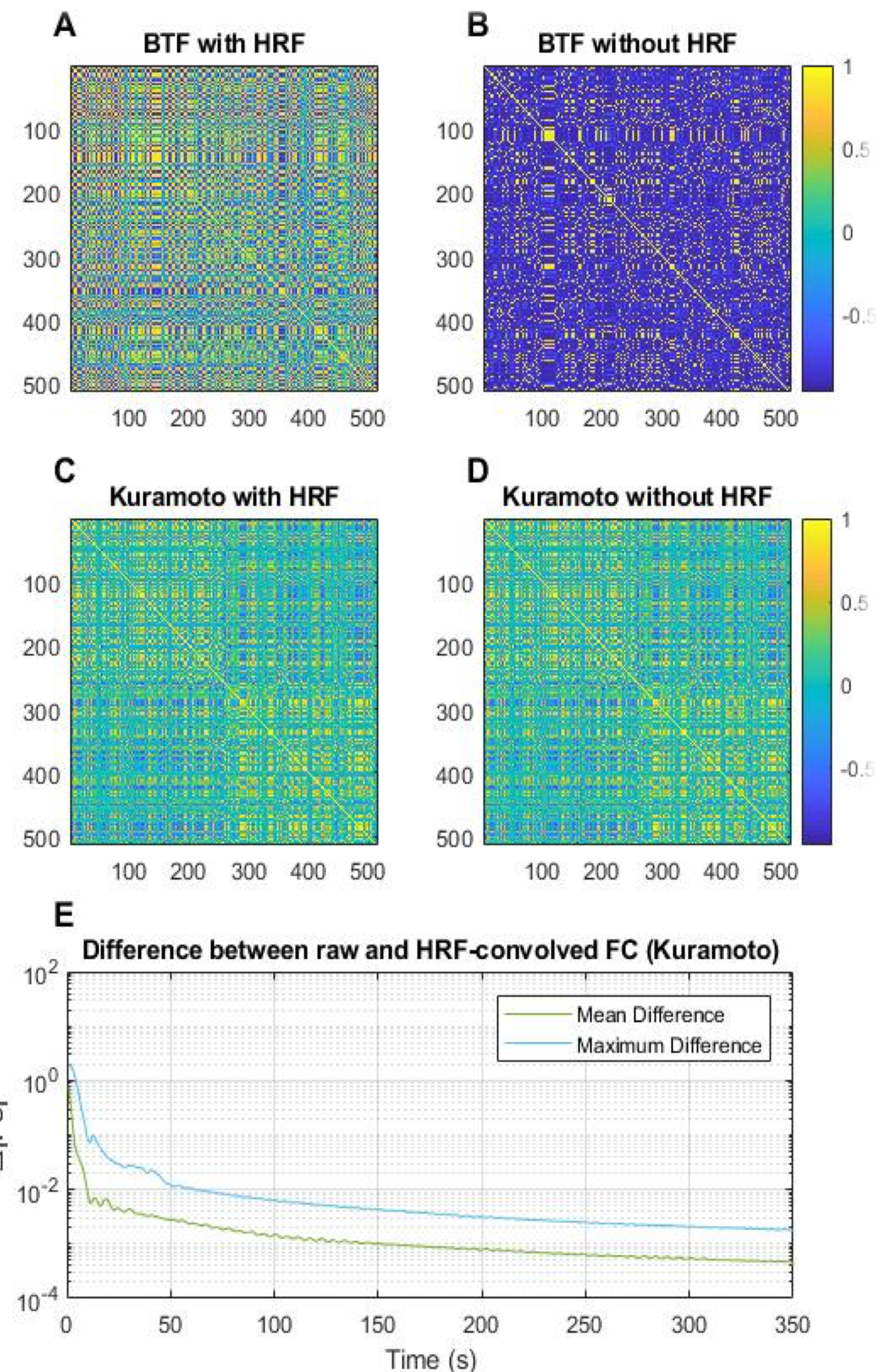
We simulated whole-brain dynamics using the mouse and human connectomes. Human brain connectivity data was obtained from diffusion images of 75 healthy adults aged 17-30 years (47 females). The diffusion MRI data were acquired on a Philips 3 T Achieva Quasar Dual MRI scanner using a single-shot echo-planar imaging (EPI) sequence (TR = 7767 ms, TE = 68 ms). Connectivity matrices were reconstructed between 513 uniformly-sized cortical and subcortical regions using probabilistic tractography (Roberts, et al., 2016).

$$\frac{dx_j}{dt} = [a_j - x_j^2 - y_j^2] x_j - \omega_j y_j + G \sum_{i=1}^N C_{ij}(x_i - x_j) + \beta \eta_j(t)$$

$$\frac{dy_j}{dt} = [a_j - x_j^2 - y_j^2] y_j + \omega_j x_j + G \sum_{i=1}^N C_{ij}(y_i - y_j) + \beta \eta_j(t)$$

Results

Our findings reveal a time- and frequency-dependent necessity of the HRF convolution in computational models of brain activity. Specifically, we show that models exhibiting faster oscillations (10-120 Hz) require the convolution with the HRF as their FC differs significantly from that of its HRF-excluding counterpart (Fig. 1A, 1B). For slow oscillations (0.01-0.1 Hz), however, this difference becomes negligible after only a short period of simulation time (Fig. 1C, 1D), with both the mean and maximum $\Delta|FC|$ decreasing below 10^{-2} after approximately 10 and 50 seconds, respectively (Fig. 1E).



Conclusion & Future Work

Modeling brain function, particularly with a large number of neurons or regions, poses a great computational challenge. Thus, previously developed models have been kept as simple and comprehensible as possible. Our study demonstrates that one way of achieving such model simplicity is to exclude the HRF convolution from models exhibiting slow oscillatory activity over longer time windows, as the results are similar in any case. By contrast, short windows typically used for time-resolved FC (Zalesky, et al., 2014) or models with fast oscillations are not eligible for this simplification step and require the convolution with the HRF.

References

1. Friston KJ, Josephs O, Rees G & Turner R, 2005. Nonlinear event-related responses in fMRI. *Magnetic Resonance in Medicine*, 39, 41-52.
2. Deco G, Kringelbach ML, Jirsa VK & Ritter P, 2017. The dynamics of resting fluctuations in the brain: metastability and its dynamical cortical core. *Scientific Reports*, 7, 3095.
3. Roberts, JA, Perry A, Lord AR, Roberts G, Mitchell PB, Smith, RE, Calamante, F & Breakspear M, 2016. The contribution of geometry to the human connectome. *NeuroImage*, 124, 379-393.