

Modeling reaction times in event-related fMRI designs

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INTRODUCTION

The use of rapid event related designs is becoming more widespread in fMRI research. The most common method of modeling these events is by convolving a hemodynamic response function with a series of impulses representing neural or cognitive events (1). This does not take into consideration how activation varies with the duration of these events.

A natural way to model neural or cognitive events is by constructing input functions of boxcars whose length varies with the reaction time (RT) on each trial (the *epoch approach*). However, this method is rarely used. A common simplification is to use RTs to modulate the height of the impulse function (the *parametric modulation approach*). It is widely assumed that this method is adequate for brief events (with RTs less than 4 s). Here we show that the epoch approach markedly increases statistical power in analyses of event-related activity and thus represents a substantial improvement over most popular methods.

METHODS

Simulations:

Simulated activations were based on the variable epoch model + AR(1) noise. Run duration was equal to 330 sec with TR=2s. Event durations were drawn from a $\Gamma(1.71, 0.49)$ distribution, whose parameters were estimated from psychophysical data from ten subjects performing a categorization task (4). The intertrial interval was randomly jittered from 3-7s.

fMRI:

Subjects were scanned in a 1.5T GE Twinspeed Scanner while passively viewing flashing checkerboards. Stimulus durations were randomly generated using the same RT-based gamma distribution as in the simulations.

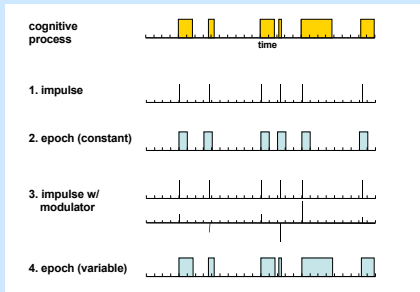


Fig. 1 – We tested the efficacy of four regression models against a hypothetical cognitive process which varied in duration on each trial. The *constant epoch* model has a constant duration equal to the TR. The *impulse with modulator* model uses a modulator impulse function whose height is proportional to the duration of the cognitive process. All of the models were convolved with the canonical double gamma hemodynamic response function (2,3).

Two reasons that the impulse function may be suboptimal:

1. Impulse model assumes constant hemodynamic response size for all trials.

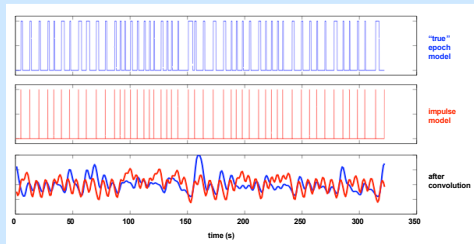


Fig. 2 – The noise-free impulse model was compared to the “true” epoch model. Even in the absence of noise, the impulse function with constant response sizes does not fit the data with variable response sizes.

2. Impulse model assumes a constant shape of hemodynamic responses for all trials.

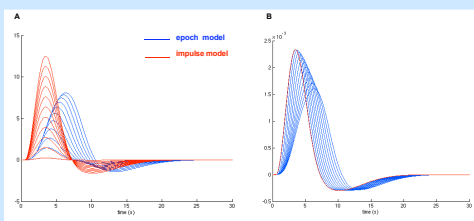


Fig. 3 – (A) The canonical HRF was convolved with either an impulse of variable height (red) or an epoch of variable duration (500-5000ms; blue). The shape of the hemodynamic response shows significant differences as a function of stimulus duration. (B) Response were normalized to unit area under the curve to demonstrate the degree of shape deviation. The red curve represents the impulse response.

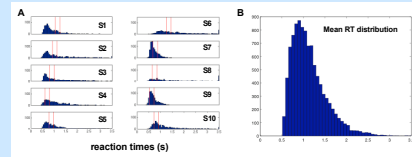


Fig. 4 – Simulating cognitive event durations. In a previous experiment (Grinband, Hirsch & Ferrera, Neuron 2006), subjects categorized line segments as “long” or “short”. We estimated the duration of categorical decision process by using the subject’s reaction time for each trial. (A) Reaction time histograms are plotted for the 10 subjects. (B) Each subject’s RT distribution was fit to a gamma function. The overall mean gamma function was used to generate random event durations for the simulations.

Variable epoch model has greater statistical power than all individual regressors

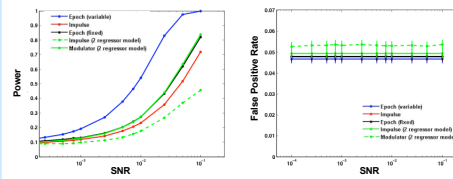


Fig. 5 – Simulated power and false positive rate for the four model types. Each data point consists of 10000 simulated runs. Error bars represent standard deviation (note: too small to be visible on left figure).

Is there any linear combination of the impulse and modulator regressors that fits the data better than the variable epoch model?

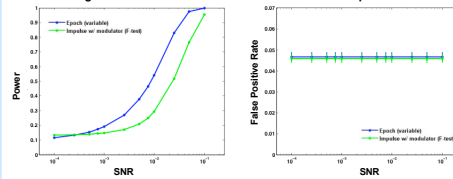


Fig. 6 – The single regressor, *variable epoch* model is more sensitive than the two regressor, *impulse with modulator* model.

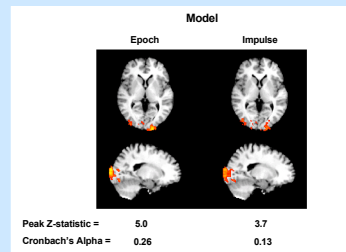


Fig. 7 – Detection of brain activity is affected by model type. Figure shows a fixed effects group analysis from a single subject who passively watched a variable duration flashing checkerboard stimulus. The epoch model showed higher z-statistics than the impulse model. Furthermore, the pattern of activity was more consistent across the 5 runs, as measured by Cronbach’s Alpha. Note, low alpha is due to the fact that the measurement was taken across all voxels.

Disadvantages of the impulse and modulator models:

1. The impulse model assumes that the neural or cognitive events have a 0-duration. This is not physiologically plausible.
2. The impulse model has the worst sensitivity of the models tested.
3. Apparent non-linearities in hemodynamic response as a function of signal strength, condition type, or population type, may actually be due to decreasing fits of the model to the data.
4. For the impulse with modulator model, it is difficult to interpret the parameters independently when the fit depends on multiple regressors for the same events. Furthermore, it is difficult to interpret activity in voxels that are significantly related to the modulator regressor, but that do not have monotonically increasing or decreasing activity.

Advantages of the variable epoch model:

1. Straight forward interpretation – i.e. BOLD activity is more likely to be related to the duration of a neuronal or cognitive process.
2. Higher statistical power than the three other models.
3. Low false positive rate.
4. Shows greater consistency across runs than the other models.

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