Optimization of Experimental Design in fMRI: a general framework using a genetic algorithm

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Abstract We describe a method for selecting design parameters in fMRI that maximizes statistical power and psychological validity. Our approach uses a genetic algorithm (GA), a class of flexible search algorithms that optimize designs with respect to single or multiple measures of fitness. We consider three fitness measures: contrast estimation efficiency, hemodynamic response estimation efficiency, and stimulus sequence counterbalancing. Although there are inherent trade-offs between these three fitness measures, our GA optimization produces designs that are well above random designs on all three criteria simultaneously.

Introduction

Block designs offer as much as a 10:1 statistical power advantage over randomized, single-trial designs in fMRI studies (1). However, these designs do not allow researchers to estimate the hemodynamic response, and their predictable nature makes them psychologically unsatisfactory for many tasks. Optimized, pseudo-random designs can provide a balance between statistical power and psychological interpretability.

Previous approaches to optimization have considered a narrow range of possible parameter values and design types, often excluding factors such as temporal autocorrelation of fMRI noise, nonlinearity in observed signal, the presence of multiple conditions and multiple contrasts of interest within a single experiment, experiment-related factors such as psychological probes that influence the design but are difficult to model, and factors such as counterbalancing of stimuli and repeated presentations that influence the psychological validity of the task (1,2,3,4). The flexibility of the genetic algorithm as an optimization tool, combined with novel methods for estimating signal nonlinearities, allows us to circumvent all of these limitations.

Two strengths of the GA framework are that a) it operates with flexible inputs, allowing for very specific modeling of experimental conditions, including non-standard trial types and experimentally observed scanner autocorrelation, and b) it is flexible with respect to fitness criteria, allowing optimization over known or novel fitness measures. We describe how genetic algorithms may be applied to design for fMRI, and we use the framework to explore the space of possible fMRI design parameters, with the goal of providing information about optimal design choices for several types of designs. In our simulations, we considered three fitness measures: contrast estimation efficiency, hemodynamic response estimation efficiency, and stimulus sequence counterbalancing.

Methods

We defined efficiency as the inverse of the variance of the contrast estimates (2,5), computed as:

$$\xi = 1/(\mathbf{wCZ^{-}SV_iS^{T}Z^{-}C^{T}})$$

Where Z^{-} is the pseudoinverse of the filtered model matrix, S is the smoothing filter applied to the model and data, C is a matrix of contrasts of interest, V_i is the intrinsic (noise) autocorrelation matrix, and w is a user-input weighting function for contrasts indicating the relative importance of each contrast of interest in the study. For contrast estimation efficiency, the model matrix Z contains delta functions for each trial type convolved with a canonical hemodynamic response function (HRF). For HRF estimation efficiency, the model matrix is a deconvolution matrix that estimates a 12 s hemodynamic response for each trial type. Higher efficiency (ξ) scores indicate lower error variance and greater signal to noise ratio.

Counterbalancing fitness is measured by the sum of squared differences between the actual and ideal frequencies with which each trial type follows each other one, up to k time steps back.

Results and Discussion

Figure 1 compares random designs (lines) with GA optimized designs and block designs (points) on all three fitness measures. GA optimizations were performed for single fitness measures contrast efficiency (eff), HRF estimation efficiency (hrf), stimulus order counterbalancing (cbal), or combinations of these.

Previous research has suggested that there is a direct trade-off between power to detect a contrast estimate the shape of the HRF (4). Our simulations reflect this limitation (Fig.1: cf. block & HRF), but show that we can obtain designs that possess efficiency for both contrast and HRF estimation (Fig. 1: eff hrf). In addition, the GA procedure is much more effective than a random search of the design space.

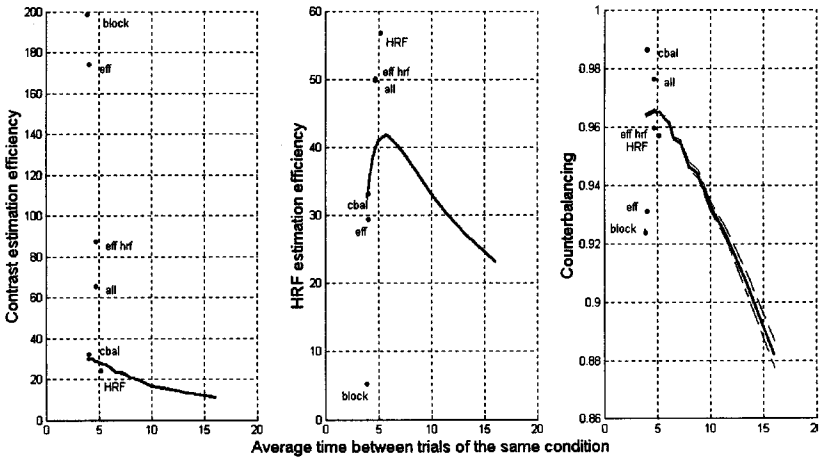

Figure 1. Optimized and block designs (black dots) compared to random sequences (black lines) on three fitness measures: a) contrast detection efficiency, b) HRF estimation efficiency, and c) counterbalancing. Standard error bars for 1000 random designs at each time point on the graphs are all within the thickness of the black line. Optimizing for a particular fitness measure produces significant costs in other fitness measures. Optimizing for multiple measures produced designs that were well above random designs on all optimized measures, but not as good as is possible with selective optimization.

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