A comparison of effective connectivity results obtained from structural equation modeling, autoregressive analysis, and Granger causality using simulated fMRI data

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INTRODUCTION

Structural equation modeling [1] (SEM) is currently the most popular method for calculating effective connectivity from fMRI data. Several papers have outlined drawbacks with applying SEM to fMRI data, namely that it requires an a priori anatomical model and it assumes instantaneous connections. Autoregressive analysis [2] (AR) has been proposed as an alternative method for calculating effective connectivity that does not suffer from the same drawbacks as SEM. More recently Granger causality [3] has been used as a summary measure of results obtained from AR analysis. No comparison of SEM, AR, and Granger causality has been published in the literature. We present a comparison of the three methods using simulated fMRI data to determine whether any technique has a distinct advantage over the other.

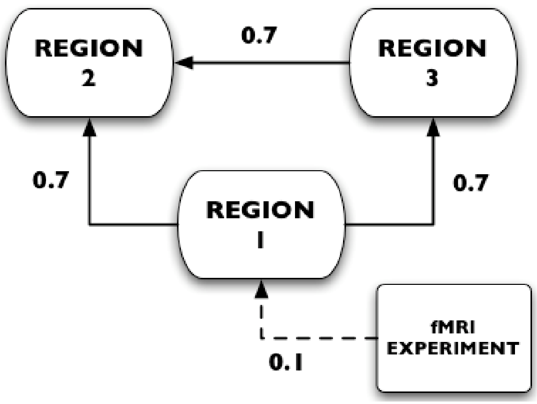

Figure 1: Diagram of three-region system used to create DCM time series. The solid lines indicate intrinsic connections, shown with a path weight of 0.7 as an example. The dashed line indicates an extrinsic connection, shown with a path weight of 0.1.

METHODS

Functional MRI time series were simulated using the dynamic causal modeling [4] (DCM) simulation code supplied with SPM2 (Wellcome Dept. of Cognitive Neurology, London, UK). A simple three-region DCM system with three connections was modeled using a standard block design. The block design was applied as an extrinsic connection to Region 1 with a constant weight of 0.1. Unidirectional intrinsic connections were set up between Region 1 and Region 2, Region 1 and Region 3, and Region 3 and Region 2; Figure 1 shows a diagram of the system. The weights of the intrinsic connections were uniformly varied from 0.1 to 0.9. Path weight values for each method were estimated 1000 times using Matlab. The autoregressive analysis was run using the Matlab based code provided by Neumaier and Schneider [5]. The Granger causality value was estimated following the work done by Geweke [6-7] and Roebroeck et. al. [8].

RESULTS

Figures 2 shows a graph of the mean path weight values from the connectivity simulations for a TR of 1 sec. One can immediately see none of the methods reproduce the modeled path weight exactly. Structural equation modeling has the largest dynamic range, suggesting it would be the most sensitive to small changes in path weight strength. Autoregressive analysis and Granger causality both demonstrate saturation at higher path weights. Additionally, contrary to the previous literature [8] on AR and Granger causality that suggested increasing the sampling rate would improve path weight estimates, decreasing the TR of the DCM model from 2 sec to 1 sec does not significantly improve the path weight estimates from these two methods.

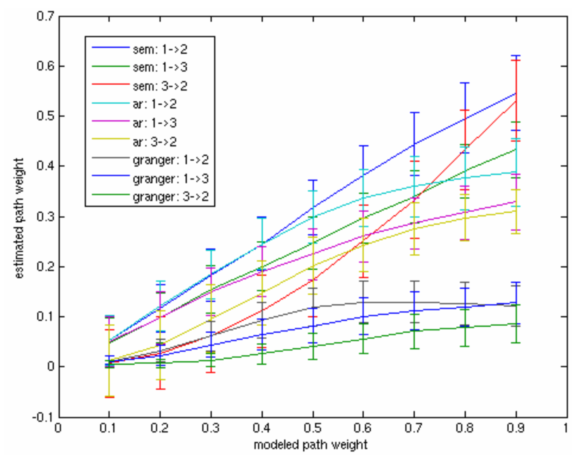

Figure 2: Graph of modeled path weight versus mean estimated path weight for the three methods considered for a DCM model with TR = 1 sec.

CONCLUSIONS

This initial comparison among structural equation modeling, autoregressive analysis, and Granger causality shows that neither autoregressive analysis nor Granger causality has a distinct advantage over structural equation modeling, despite the drawbacks of applying SEM to fMRI data. In fact, where the path model is specified correctly, SEM may have an advantage over AR for detecting small changes in connectivity.

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