A comparison of the abilities of structural equation modeling, autoregressive analysis, and Granger causality to detect path weight differences in effect connectivity results calculated from real fMRI time series data

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INTRODUCTION

Structural equation modeling (SEM), autroregressive analysis (AR), and Granger causality (GC) are three commonly used methods for calculating effective connectivity from fMRI data. As effective connectivity analyses become more common, it is important to understand how these computational methods compare with each other in terms of their abilities to detect changes in path weight values between tasks or subjects. As, yet no direct comparison of these methods has been published in the literature. We present an assessment of the three aforementioned methods using real fMRI data to determine if any has a distinct advantage over the others in quantifying changes in path weight values.

METHODS

Data were acquired on eight healthy, right-handed adults on a 1.5T scanner (Signa LX; GE Medical Systems, Milwaukee, WI). A single-shot gradient-recalled echo-planar pulse sequence (TR/TE = 1750/40 msec) with FOV = 24 cm and a 64x64 matrix was used to acquire 23 axial slices (5mm/1mm) yielding whole brain coverage. All subjects gave informed consent, and all successfully completed the study. FMRI data was collected for two bimanual finger tapping tasks; each task consisted of alternating 20 second blocks of rest and tapping and lasted for 3 minutes and 40 seconds. The finger tapping tasks were: (TASK 1) tapping both index fingers, simultaneously, and (TASK 2) tapping both index fingers, alternating hands, both at a self-determined pace. Data for each subject were corrected for motion, normalized to the ICBM template, smoothed with an 8 mm FWHM Gaussian, and processed using SPM5 (Wellcome Department of Cognitive Neurology, London, UK). Time series for each of the regions shown in Figure 1 were extracted using SPM5 with the aid of the wfu_pickatlas tool [2-3] and its built-in aal atlas [4]. The SEM path weights were estimated R: A Language and Environment for Statistical Computing (R Development Core Team 2006); the AR and Granger causality path weights were estimated in Matlab (The MathWorks, Natick, MA, USA) using the arfit package [5] and the methodology laid out by Goebel et. al. [6], respectively. Path weights were calculated for each subject, and the results were averaged to produce a single, mean path weight for each method. Due to the small sample size and the small dynamic range of the results, traditional null hypothesis significance testing has been abandoned in favor of effect size [1] as a statistical measure of the ability of these computational methods to detect changes in path weight. Effect size was measured using Cohen's *d* [7] with the Hedges and Olkin [8] correction for small sample bias. Confidence intervals (CI) were calculated at significance level of 90%.

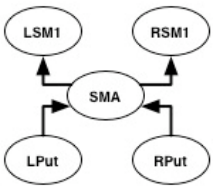

Figure 1: Path model used to guide connectivity analyses for all three methods. LSM1 and RSM1: left/right sensorimotor cortex; SMA: supplementary motor area; LPut and RPut: left/right putamen

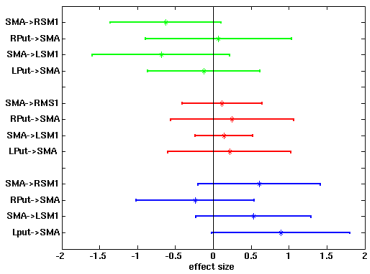

Figure 2: Graph of effect size and 90% CI of path weight difference for the two tasks (TASK 1-TASK 2) for each path for each method. SEM results shown in BLUE, AR in RED, and GC in GREEN.

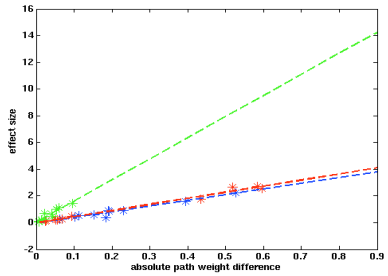

Figure 3: Graph of absolute path weight difference versus effect size for all methods. SEM results shown in BLUE, AR in RED, and GC in GREEN. Linear fits of the data are indicated by the dashed lines.

RESULTS

Table 1 lists the mean path weights differences between the two tasks for each computational method. In line with the findings from the simulated data, the SEM results exhibit a larger dynamic range than either the AR or GC results, suggesting that SEM would be better at detecting small changes in path weight than either AR or GC. However, the effect sizes shown in Figure 2 seem to indicate that GC should be able to detect changes in path weights as well as SEM, as evident by the similar effect sizes between the two methods. The uniformly small effect sizes for the AR results would seem to indicate that this method may not be as sensitive to path weight changes as the other two methods. Figure 3 shows a graph of absolute effect size versus absolute path weight difference along with a linear fit for each of the three methods, where the absolute path weight differences were acquired by calculating all possible differences among the eight mean path weights of the two finger tapping tasks. These results confirm that GC detects changes differences in path weights as well or better than either SEM or AR, despite the small, relative size of the path weight differences shown in Table 1. The results also suggest, contrary to what is seen in Figure 2, that AR and SEM should perform equally well in detecting small changes in path weight differences.

CONCLUSIONS

The results of comparing SEM, AR, and Granger causality using real fMRI data indicate, that while the path weight differences estimated using Granger causality and AR may be uniformly small and not directly comparable to each other or those estimate using SEM, both AR and GC perform as well or better than SEM in detecting small path weight differences. This in despite of SEM having the apparent advantage of having a larger dynamic range and larger estimated path weight differences. We have shown that all three methods, SEM, AR, and GC, are all appropriate methods for calculating effective connectivity from fMRI data, and all are able to detect changes in path weights, including small changes.

Table 1: List the mean path weight differences and standard deviations for the four paths in Figure 1 for the two tasks considered.

	LPut->SMA	SMA->LSM1	RPut->SMA	SMA->RSM1
SEM	0.2±0.3	0.1±0.3	-0.06±0.3	0.15±0.3
AR	0.05±0.3	0.03±0.2	0.07±0.4	0.02±0.3
GC	-0.01±0.09	-0.02±0.04	0.01±0.13	-0.04±0.09

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