6-5-2012 12:00 AM

Toward a Functional Characterization of Cognitive Control Networks

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Graduate Program in Neuroscience
A thesis submitted in partial fulfillment of the requirements for the degree in Master of Science

TOWARD A FUNCTIONAL CHARACTERIZATION OF COGNITIVE CONTROL NETWORKS

(Spine title: Functional characterization of cognitive control networks)

(Thesis format: Monograph)

by

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Graduate Program in Neuroscience

A thesis submitted in partial fulfilment
of the requirements for the degree of
Master of Science

The School of Graduate and Postdoctoral Studies
The University of Western Ontario
London, Ontario, Canada

THE UNIVERSITY OF WESTERN ONTARIO
SCHOOL OF GRADUATE AND POSTDOCTORAL STUDIES

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entitled:

Toward a Functional Characterization of Cognitive Control Networks

is accepted in partial fulfillment of the
requirements for the degree of
Master of Science

Date_____

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Chair of the Thesis Examination Board

ABSTRACT

Cognitive control is an executive process that has been associated with a distributed set of cortical regions. These distributed regions appear to cluster into distinct networks with dissociable functions. In this study, independent component analysis was used as a tool to investigate functional connectivity in event-related fMRI data. Extracted networks of interest were functionally characterized using a hybrid task that independently probed moment-to-moment adjustments in control, and stable task-set maintenance. A cinguloinsular network was implicated in the processing of moment-to-moment adjustments in control based on its activation patterns during this task. Subsequently, functional connectivity between two networks previously implicated in control, two default mode networks, and a visual network were investigated overall, and in specific condition windows. Findings from this study emphasize the utility of independent component analysis in directly functionally characterizing dissociable cognitive control networks.

KEYWORDS: Functional connectivity, functional network, executive control, cognitive control, independent component analysis, functional magnetic resonance imaging (fMRI), stable task-set maintenance, adaptive control, frontoparietal, cinguloinsular

CO-AUTHORSHIP STATEMENT

Portions of the introduction section of this thesis (as indicated) have been submitted for publication in the co-authored paper, ‘Age-Related Changes in Functional Connectivity in a Cognitive Control Network.’ Frederick Ezekiel was the primary author on these sections of the article.

Portions of the methods section and results section of this thesis (as indicated) have been published in the co-authored paper ‘Brain regions associated with moment-to-moment adjustments in control and stable task-set maintenance.’ Frederick Ezekiel was the primary author on the methods portion of this article. Frederick Ezekiel, Heather Wilk, and J. Bruce Morton jointly contributed to the writing of the behavioural results section of the article.

ACKNOWLEDGEMENTS

Thank you to the following individuals:

Dr. J Bruce Morton (Supervisor) - consistent support throughout this project.

Dr. Tom Eichele (Collaborator, Bergen University) – advice on the independent component analysis design and data structure, and providing scripts for the analysis of between network functional connectivity.

Heather Wilk (Lab Colleague) – Data collection.

Christian Battista (Lab Colleague) – Technical support during the analysis phase of this project.

Katie Knapp (Lab Colleague) – Support and ideas throughout this project.

Haitao Yang (Brain and Mind Institute) – Technical support during the analysis phase of this project.

Deanna Sharp & Paula Raben (Undergraduate Research Assistants) – Data organization.

I would also like to thank the Morton and Ansari labs, and all of their members for creating a fun, enriching, and stimulating environment in which to work and learn.

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LIST OF ABBREVIATIONS

ACC	Anterior Cingulate Cortex
AI	Anterior Insula
BOLD	Blood Oxygen Level Depdendent
CAE	Conflict Adaptation Effect
CCN	Cognitive Control Network
CI*	Cinguloinsular
CP	Cingulopercular
dlPFC	Dorsolateral Prefrontal Cortex
dPMC	Dorsal Premotor Cortex
FC	Functional Connectivity
fMRI	Functional Magnetic Resonance Imaging
FO	Frontal Operculum
FP	Frontoparietal
GLM	General Linear Model
IFJ	Inferior Frontal Gyrus
INC	Intrinsic Network Connectivity
IPC	Inferior Parietal Cortex
IPL	Inferior Parietal Lobule
PFC	Prefrontal Cortex
PPC	Posterior Parietal Cortex
pSMA	Presupplementary Motor Area
lFP*	Left Frontoparietal
SN	Salience Network
TCN	Temporally Coherent Network
vmPFC	Ventromedial Prefrontal Cortex

*lFP and CI are terms used to describe networks extracted in this study. The lFP network includes regions that overlap with ECN (Seeley et al., 2007) and FP (Doesenbach et al., 2008) networks. The CI network includes regions that overlap with the SN (Seeley et al., 2007) and CP (Dosenbach et al., 2007) network.

Chapter 1 - Introduction

1.1 Preamble

Cognitive control refers to the processes that guide perceptual and motor selection, particularly when faced with conflicting sources of information or task-inappropriate response tendencies (Miller & Cohen, 2001; Wilk et al., 2012). Evidence supports that control processes are supported by a distributed set of cortical regions (Wilk et al., 2012; Botvinick et al. 2001; Cole & Schneider, 2007). A distinction in control processes has been made in the cognitive control literature based on the timescales on which the processes operate (Dosenbach et al., 2007, 2008). Moment-to-moment adjustments in control are dynamic changes that occur over short timescales in response to changing environmental demands; alternatively, stable task-set maintenance is a control process that operates over longer timescales to support appropriate behavior under stable environmental conditions (Dosenbach et al., 2007, 2008). In this study, cortical networks supporting control processing and how they respond to different cognitive demands are investigated using a hybrid fMRI task; this task probed moment-to-moment adjustments in control and stable task-set maintenance independently (Wilk et al., 2012).

1.2 Probing Stable Task-set Maintenance and Adaptive Control

In order to independently probe stable task-set maintenance and adaptive control, we developed a hybrid conflict adaptation task (Wilk et al., 2012). The

task was implemented in a hybrid block-event related design to enable independent modeling of both phasic (event-related) and tonic (block-level) signal changes (Wilk et al., 2012; Visscher, et al. 2003). This involved parametrically varying the frequency of compatible trials at the block level (75%, 50% and 25%), in a size congruency number comparison task. Participants were asked to select the numerically larger of two numbers presented on a screen. On compatible trials, the numerically larger number was also physically larger. On incompatible trials, the numerically larger number was physically smaller. Participants were typically slower and less accurate when responding to incompatible trials – this is referred to as an interference effect. Interference effects become less pronounced as the frequency of compatible trials decreases – this frequency-based influence on the interference effect is referred to as the conflict adaptation effect (CAE – Banks & Flora, 1977; Borgman et al., 2011; Henik & Tzelgov, 1982).

This block level frequency manipulation introduced parametrically varied demands on task-set maintenance and moment-to-moment adjustments in control. When the frequency of compatibility is high, the physical size of the digits becomes a more reliable cue, enabling participants to rely on both numerical and physical size to make an accurate decision. When incompatible trials are presented during these blocks, a greater adjustment is necessary in the moment to attend solely to the numerical dimension of the stimulus; under these conditions, there is an increased demand on moment-to-moment (dynamic) control processing (Wilk et al., 2012). In blocks where compatible trials are

infrequent, participants form a stronger task-set which involves attending only to the numerical magnitude of the stimulus. In these blocks, participants experience conflict between the numerical magnitude and physical magnitude on most trials. Subsequently, the task-set that involves identifying the numerically larger digit must be maintained actively to enable accurate responses; this block level frequency condition leads to increased demands on stable task-set maintenance (see figure 1 - Wilk et al., 2012).

1.3 Cortical Substrates of Stable Task-set Maintenance and Adaptive Control

Using these probes, regions involved in both moment-to-moment adjustments in control, and stable task set maintenance were identified in a standard voxel-wise General Linear Model (GLM) fMRI analysis (Wilk et al., 2012). Regions involved in moment-to-moment adjustments included bilateral anterior insular cortex (AIC), right anterior cingulate cortex (ACC), bilateral dorsolateral prefrontal cortex (dlPFC), and right inferior parietal cortex (IPC). Regions involved in stable task-set maintenance included the medial superior frontal gyrus (Wilk et al., 2012). This study, including its novel approach to probing functional dissociations using a hybrid task, offered a promising advance in identifying regions involved in dissociable cognitive control demands. However, in a voxel-wise GLM the betas for each predictor included in the linear regression are calculated for each voxel independently. A subsequent voxel-wise t-test determines whether a predictor for a condition of interest statistically differs from a predictor representing control conditions. As a result, the regions identified

in a voxel-wise GLM are not necessarily functioning in unison, or engaging in related activity; this analysis identifies voxels that are independently involved in a specific aspect of the task. These regions could therefore not be described as a functionally integrated cortical network without statistically assessing relationships between the voxels involved. Several tools have been developed to assess such relationships.

1.4 From Distributed Regions to Cortical Networks

The growth of analytical tools to study functional connectivity in the human cortex has enabled the identification of a functionally coupled set of regions sometimes referred to as the Cognitive Control Network (CCN – Cole & Schneider, 2007; Duncan & Owen, 2000). Regions involved in this network include ACC (pre-supplementary motor area – pSMA), dlPFC, inferior frontal junction (IFJ), AIC, dorsal pre-motor cortex (dPMC), and posterior parietal cortex (PPC). Regions within the CCN demonstrate higher functional connectivity, as measured by timecourse correlations in resting fMRI data, than the average functional connectivity between any of the regions and a set of randomly selected non-CCN cortical regions (Cole & Schneider, 2007). Furthermore, these regions appear to coactivate in the face of cognitively demanding tasks (Cole & Schneider, 2007; Duncan & Owen, 2000). Many regions appear to be implicated in the CCN; furthermore, dissociations have been identified in control processes based on their timescale (Dosenbach et al., 2007, 2008). This raises the question as to whether control is processed by a single CCN, or multiple networks involved in processing different aspects of control.

The dual-networks account (Dosenbach et al., 2007, 2008) proposes that the CCN consists of two dissociable networks, identified using graph theoretic approaches; these include a frontoparietal (FP) network and a cingulopercular network (CP). Both networks demonstrate small-world characteristics, with strong short-range within network connections, and weaker long-range between network connections. This account proposes that the FP network, consisting of dlPFC, inferior parietal lobule (IPL), dorsal frontal cortex (dFC), inferior parietal cortex (IPC), precuneus, and middle cingulate cortex (mCC), is related to moment-to-moment adjustments in control processing. The CP network, consisting of anterior PFC, AI/FO, dorsal ACC, and thalamus, is related to stable task-set maintenance. These functional characterizations stem from a review of univariate and single cell recording studies which ascribe functions to specific regions identified in these networks (Johnston et al., 2007; Liston et al., 2006; MacDonald et al., 2000; Rushworth et al., 2007; Sakai & Passingham, 2007).

Another approach to functionally characterizing dissociable CCN's involves correlating measures of connectivity within a network with measures from offline tasks that probe cognitive abilities and behavioural tendencies (Seeley et al., 2007). In Seeley et al. (2007) networks were identified using two converging approaches: independent component analysis (ICA), and a region of interest (ROI) based functional connectivity analysis. Intrinsic network connectivity (INC) was used to define within network connectivity. This measure involved calculating the average pearson correlation coefficient by correlating timecourses between two nodes within a network. Correlations between

individual differences in these correlation coefficients and offline measures of prescan anxiety, and performance on an executive control task could then be used to characterize the function of these networks. A ‘salience network’ network included the dACC, orbital frontoinsular cortices, and several subcortical and limbic structures including the thalamus; this network included many regions that overlap with those in the CP network (Dosenbach et al., 2007, 2008). INC measures between dorsal ACC and dlPFC nodes of the salience network correlated with prescan anxiety measures, leading to the characterization of this network as a salience network. An ‘executive control network’ (ECN) included dlPFC and lateral PPC; this network included many regions that were also involved in the FP network (Dosenbach et al., 2007, 2008). INC measures between the lateral parietal nodes of this network correlated with offline executive task performance, leading to the characterization of this network as an executive control network.

Consistent spatial dissociations have been identified within the cognitive control network. Cinguloinsular (CI – including the SN and CP network) and FP networks appear to be relatively independent functional cortical networks, which are involved in different aspects of cognitive control (Dosenbach et al., 2007, 2008; Macdonald et al., 2000; Seeley et al., 2007). Inconsistencies in the specific functional characterization of these networks across studies could stem from the indirect association between network topography and function. Resting state fMRI data can be paired with graph theoretic approaches, region of interest FC analyses, and independent component analysis to characterize the structural

parameters and topography of these networks. Furthermore, regions within these networks have been functionally characterized through the standard voxel-wise GLM analyses discussed above (Wilk et al., 2012). However, more direct functional characterizations can arguably be made by assessing the function of large-scale networks in an event-related design. With recent developments in tools for analyzing fMRI data, it has become possible to assess the function of a whole network in event-related data.

1.5 Functionally Characterizing Cortical Networks

Independent component analysis (ICA) is a statistical method used to identify systematically independent sources of variance in mixtures of data; in fMRI, ICA can be used to identify said independent sources, or components, under spatial or temporal (or a combination thereof) domains (Calhoun et al., 2003). ICA identifies components that are derived from statistically independent sources; for fMRI analysis, spatial patterns of activation form components based on their non-Gaussian independence from one another (Calhoun et al., 2003). Calhoun et al. (2003) suggest that spatial ICA is particularly effective for cognitive tasks that are characterized by distributed activation patterns. Following identification of independent spatial components, each component's respective timecourse is back-reconstructed. Back-reconstructed timecourses indicate the degree to which each spatial component contributes to the raw data in each volume (Calhoun & Adali, 2006). While components are maximally independent from one another, residual covariance remains between component timecourses,

enabling subsequent analyses of between-component FC. Combined, these analyses enable us to move from a raw set of fMRI data, to an fMRI dataset that has been organized into independent spatial components, or functional networks, that have an associated timecourse. Objective selection of theoretically meaningful components can be achieved by spatially correlating component topographies with a network template from the existing cognitive control literature, temporally correlating a timecourse with a predictor from a design matrix, or both (Ezekiel & Morton, Submitted).

There are several advantages to the use of ICA as an analytic tool in the context of this study. First, the concept of independence maximization between components enables variance that can be attributed to artifacts (like the cardiac rhythm or subject motion) to be attributed to unique components (Calhoun & Adali, 2006; Calhoun et al., 2003). This leaves components of interest relatively free of artifactual sources of variance. Second, since ICA is typically conducted on a whole-brain scale, the components extracted from the analysis are not biased by seeds selected according to an *a priori* hypothesis (Ezekiel & Morton, submitted). Third, ICA can be applied to both resting state and event-related fMRI data with converging results (Calhoun, 2008). Independent components can therefore be extracted from event-related data in an attempt to directly functionally characterize networks that have been heavily discussed in the resting-state literature. Fourth, ICA enables us to investigate interactions (FC) between the components (or functional networks) extracted, by comparing network timecourses. This can be done to investigate overall between-network

FC, or to identify connectivity under specific task demands by comparing timecourse correlations in specific task windows.

1.6 The Current Study

In this study, spatial ICA was applied to an event-related fMRI dataset in which the hybrid conflict adaptation paradigm discussed above was administered. A spatial selection criterion was used to identify networks that related to Executive Control and Salience Networks (Seeley et al. 2007). Subsequently, a GLM analysis was conducted on the reconstructed timecourses of selected components to identify whether effects of conflict, and conflict adaptation effects manifested in the activity profiles of these networks. Identification of conflict adaption effects in a network's beta pattern would implicate that network in processing moment-to-moment adjustments in control. Networks demonstrating interference effects related to sustained signals that were not sensitive to conflict frequency could be implicated in general executive control processing (Wilk et al., 2012; Visscher, et al. 2003). Lastly, between-network functional connectivity was assessed, both overall and in specific task conditions.

1.7 Hypotheses

It was hypothesized that:

1. Stable functional networks would be identified in our event-related dataset that are spatially consistent with those that have been discussed in the resting state literature using spatial ICA.
2. Spatial correlation of network topographies would enable objective selection of a CI network from the Salience Network template and a FP network from the Executive Control Network template (Seeley et al., 2007).
3. Based on functional characterizations offered by Seeley et al., 2007, the task would elicit a pattern of betas consistent with the CAE in the CI network, while the FP network would demonstrate a typical conflict interference effect (greater responsivity to incongruence than congruence).
4. The FP network and CI network would show strong overall between-network FC, as both have been implicated in cognitive demands probed by this task. Precuneus and ventromedial PFC (vmPFC) default networks, which are both typically part of a single default network, would show high overall between-network FC.
5. Analysis of condition-specific fluctuations in FC between networks would be exploratory, as there is very little evidence to form predictions based on this type of between-network comparison.

Chapter 2 - Methods

*Note: Participants, Task and MRI Data Acquisition sections have been published in Wilk, H. A., Ezekiel, F., & Morton, J. B. (2012). Brain Regions Associated with Moment-to-Moment Adjustments in Control and Stable Task-Set Maintenance. *Neuroimage 59, 2*.

2.1 Participants

Participants included 26 right-handed young adults (12 males) who ranged in age from 21- to 35-years. All participants had normal or corrected-to-normal vision, and reported no history of neurological or psychiatric illness. Data from three participants were excluded from the analysis, one due to equipment malfunction and two due to excessive motion. Participants provided written consent to their participation prior to data collection. All aspects of the study were conducted in accordance with the Declaration of Helsinki.

2.2 Task

Participants were administered a size congruency task, in which on each trial, two white digits differing both in physical and numerical magnitude were presented simultaneously on a black background for 950ms (see *Figure 1*). Digits included numbers 1 through 9; physically large digits appeared in 60 point font; physically small digits appeared in 30 point font. On compatible trials, the numerically larger digit was physically larger. On incompatible trials, the numerically larger digit was physically smaller. Participants selected the

numerically larger of the two digits by depressing a key that corresponded with the location of the numerically larger digit (i.e., left or right) using their right hand. The response deadline was equal to the stimulus duration (950ms) and no feedback was provided. Individual trials were grouped into 16-trial blocks that differed in terms of the proportion of trials in the block that were compatible. Thus, in High-Frequency blocks, 75% of trials (or 12 of 16) were compatible; in

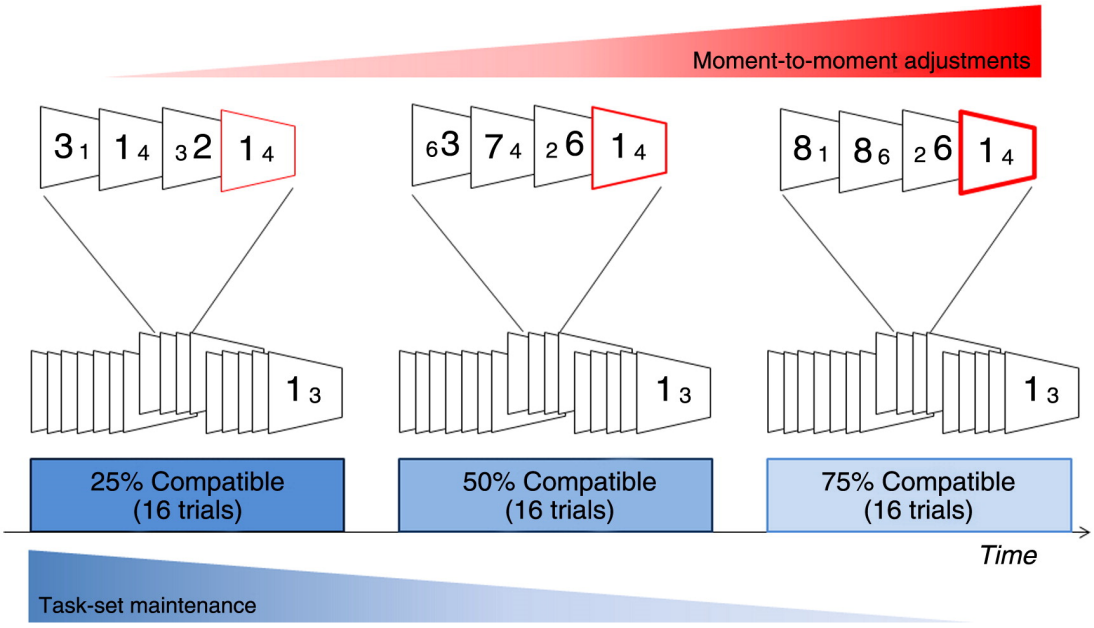

Figure 1. An illustration of the experimental paradigm. Two digits that differed in physical and numerical magnitude were presented on each trial, and participants selected the numerically larger digit by means of a button-press. On compatible trials, the numerically larger digit was physically larger; on incompatible trials, the numerically larger digit was physically smaller. Individual trials were administered with a jittered ITI in 16-trial blocks that varied in terms of the proportion of compatible trials within the condition. Demands on moment-to-moment adjustment parametrically increased with increases in the block-level proportion of compatible trials; demands on task-set maintenance increased with decreases in the block-level proportion of compatible trials (Wilk, et al., 2012).

Medium-Frequency blocks, 50% of trials (or 8 of 16) were compatible; and in Low-Frequency blocks, 25% of trials (or 4 of 16) were compatible. An additional three anchor trials were added to the beginning of each block as a means of establishing expectations about the frequency of compatible trials within the block, but were modeled separately using a predictor of no interest. For High-Frequency blocks, all three anchor trials were compatible; for Medium-Frequency blocks, either one or two trials were compatible, and for Low-Frequency blocks, none were compatible. Trials within blocks were presented in a random order that was fixed for all participants, and were randomly jittered by means of an inter-trial interval (or ITI) that ranged from 2500ms to 5500ms (M = 4000ms) in 500ms increments. Blocks were presented in a random order, fixed for all Participants, and were separated by 10-second intervals. During all inter-trial and inter-block intervals, participants remained fixated on a centrally-presented white cross. In total, individual participants completed 24 separate blocks of trials (8 each of High-, Medium-, and Low- Frequency) for a total of 384 individual trials. The entire task was administered in two separate 18-minute runs.

2.3 MRI Data Acquisition

MRI data were collected using a 3T Siemens TimTreo MRI scanner fitted with a Siemens 32-channel head coil (Siemens Medical Solutions, Erlangen, Germany). Functional volumes consisted of 36 slices acquired parallel to the ACPC axis using an interleaved slice acquisition order and an echo-planar imaging pulse sequence (TR = 2000ms, TE = 30ms, flip angle = 78°, 64 x 64

matrix, 21.1 x 21.1 cm FOV, 3 x 3 x 3mm voxel resolution). A total of 1486 functional volumes were collected from each participant over two separate 743-volume runs. In addition, a high-resolution anatomical scan (192 slices, 256 x 256 matrix, 21.1 x 21.1 cm FOV, 1 x 1 x 1mm voxel resolution) was acquired from each participant to assist in visualizing the results of functional analyses.

2.4 fMRI Data Preprocessing

Prior to preprocessing, motion along 3 directions of translation and around 3 axes of rotation were estimated for each run. Motion was constrained to a maximum of 3 mm over the entire run, resulting in the exclusion of 0 runs. Data were preprocessed using SPM8 (FIL, UCL, London, UK). Data were motion-corrected by aligning each volume of each run to the first volume of the first functional run collected. Functional scans were then warped into Montreal Neurological Institute stereotactic space (MNI, Montreal, Canada) and smoothed using an 8 mm full-width at half-maximum Gaussian smoothing kernel.

2.5 Independent Component Analysis

A spatial group ICA was conducted on all subjects' functional data using the Group ICA of fMRI toolbox for MATLAB (GIFT – MIND Research Network, Albuquerque, United States). 20 independent components were extracted in this ICA. A low model order was selected to ensure consistency in scale and spatial characteristics between the networks extracted in our study, and those extracted by Seeley et al., 2007. Prior to conducting the ICA, data were preprocessed by

removing the mean per time point in GIFT. The information maximization (Infomax) algorithm was used to extract group spatial components. This algorithm unmixes data to maximize the independence between source components extracted; at the same time, components extracted consist of voxels that demonstrate a high degree of covariance in their pattern of activation. To ensure the reliability of the spatial decomposition, the ICA was iterated 100 times with random initial weights using the ICASSO tool in GIFT. The clustering structure of the components extracted from each iteration was visualized in signal space. This tool enabled the assessment of component stability, as stable components show a high degree of clustering across iterations (Himberg, Hyvärinen, & Esposito, 2004). Group component timecourses were then back-reconstructed using the GICA3 method in GIFT. Prior to subsequent analyses, group component timecourses were intensity normalized and linearly detrended.

2.6 Component Selection

A spatial selection criterion was used to select components that were topographically consistent with functional networks discussed in the cognitive control literature. Independent spatial correlations were calculated between each component extracted from the functional data, with each of the SN and ECN templates (Seeley et al. 2007). Components involved in the default mode network were identified by correlation with a default mode network template (Bluhm et al., 2008). The best fitting component(s) (the component that yielded the highest significant spatial correlation) with each template was selected for

further analysis. A visual component was visually selected and included in subsequent analyses to see whether the patterns identified in our networks of interest were specific to networks that included regions previously implicated in cognitive control.

2.7 Functional Analysis on Components of Interest

A GLM was conducted on timecourses of selected components to identify CAEs and interference effects in task-related BOLD modulation. Design matrices were created in SPM8, and included nine independently modeled predictors representing trial types included in the hybrid task, in addition to their time derivatives (see Table 1).

Table 1. **Predictors included in design matrix**

Predictor	Description
High-Compatible	75% compatible trials Compatible - larger number is physically larger
High-Incompatible	75% compatible trials Incompatible – larger number is physically smaller
Medium-Compatible	50% compatible trials Compatible - larger number is physically larger
Medium-Incompatible	50% compatible trials Incompatible– larger number is physically smaller
Low-Compatible	25% compatible trials Compatible - larger number is physically larger
Low-Incompatible	25% compatible trials Incompatible – larger number is physically smaller
Baseline	All compatible trials in a block used to establish a baseline signal
Start	First 3 trials of each block
Other	Error trials or trials where participants did not respond within the allotted window

An ANOVA was run with condition (high, medium, or low frequency of compatibility) and trial-type (compatible or incompatible) as independent variables of interest.

2.8 Between-Network FC Analysis

Overall FC between networks was assessed by calculating timecourse correlation coefficients between each selected network. Condition-specific between-network FC was calculated by extracting timecourses from each condition window, and calculating Pearson correlation coefficients between timecourses of networks of interest during these windows. These analyses were conducted in Matlab 2010b (Mathworks, Natick, Massachusetts).

Chapter 3 - Results

*Note: The behavioral results section has been published in:
Wilk, H. A., Ezekiel, F., & Morton, J. B. (In press). Brain Regions Associated with Moment-to-Moment Adjustments in Control and Stable Task-Set Maintenance. *Neuroimage*.

3.1 Behavioural Results

Response time and accuracy are plotted in Figures 2 and 3. A 3 Condition x 2 Compatibility repeated-measures ANOVA confirmed an effect of Compatibility on response time, F (1, 22) = 80.3, $p < .05$, and accuracy, F (1, 22) = 13.7, $p <$

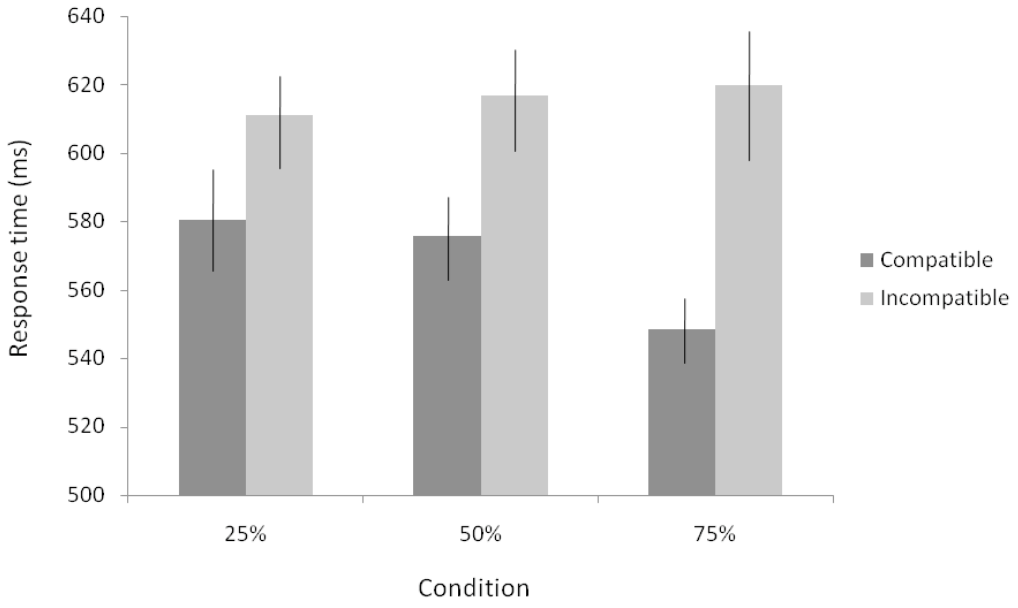

Figure 2. Response times plotted as a function of Condition (i.e., 25%, 50%, or 75% compatible) and Compatibility (i.e., Compatible and Incompatible). Error bars show one SE above and below the mean (Wilk et al., 2012).

.05, such that responses to incompatible stimuli were slower and more error-prone than responses to compatible trials. There was also an effect of Condition on response time, F (2, 44) = 4.0, p < .05, such that responses were slower in the 25% (mean RT = 596 ms) and 50% (mean RT = 596 ms) compared with the 75% (mean RT = 585 ms) conditions. Finally, there was a significant interaction of Condition and Compatibility on response time, F (2, 44) = 16.4, p < .05, and accuracy, F (2, 44) = 12.6, p < .05. Post-hoc tests (Bonferroni-corrected for multiple comparisons) confirmed that responses to compatible stimuli were faster in the 75% as compared to the 50% and 25% conditions, and more accurate in the 75% and 50% as compared to the 25% conditions.

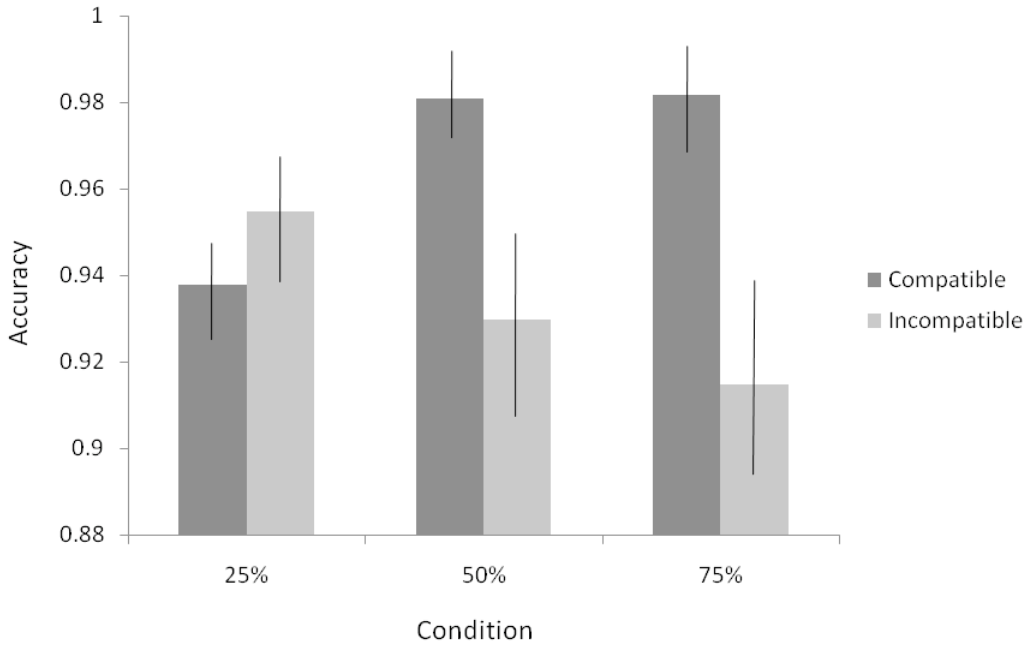

Figure 3. Behavioral accuracy as a function of Condition (i.e., 25%, 50%, or 75% compatible) and Compatibility (i.e., Compatible and Incompatible). Error bars show one SE above and below the mean (Wilk et al., 2012).

To guard against the possibility that the pseudo-randomized block order administered to all participants may have unduly influenced performance, we tested for differences in behavioral performance between blocks administered early and those administered late in the testing session. A 2 Order (early, late) x 3 Condition (25%, 50%, 75%) x 2 Compatibility (compatible, incompatible) repeated-measures ANOVA on response time revealed effects of Compatibility, F (1, 19) = 25.9, p < .01, and Condition, F (2, 38) = 6.5, p < .01, and an interaction of Compatibility and Condition, F (2, 38) = 12.1, p < .01, but no effects of Order and no higher order interactions involving Order. An identical analysis on accuracy revealed an effect of Compatibility, but no effects or interactions involving Order.

3.2 Component Selection

Of the 20 components extracted in this ICA, components that yielded the highest spatial correlation with templates from the resting state literature were selected for subsequent analyses. A CI network was selected for further analysis because it demonstrated the highest spatial correlation with the SN template (Seeley et al., 2007, r = .459, t (40) = 3.29, p < 0.01, see Figure 4). This component included regions of the anterior cingulate cortex and anterior insula. A left FP (lFP) network was selected because it showed the highest spatial correlation with the ECN template (Seeley et al., 2007, r = 0.325, t (40) = 2.173, p < 0.05, see Figure 5). Two default mode networks, one primarily composed of vmPFC (r = .308, t (40) = 2.05, p < 0.05), and another composed primarily of

precuneus (r = .309, t (40) = 2.06, p < 0.05) demonstrated the highest spatial correlation coefficients with a default mode template (Bluhm et al., 2008 - see Figures 6 and 7). Lastly, a visual component was visually selected which occupied V1 – V4 (see Figure 8).

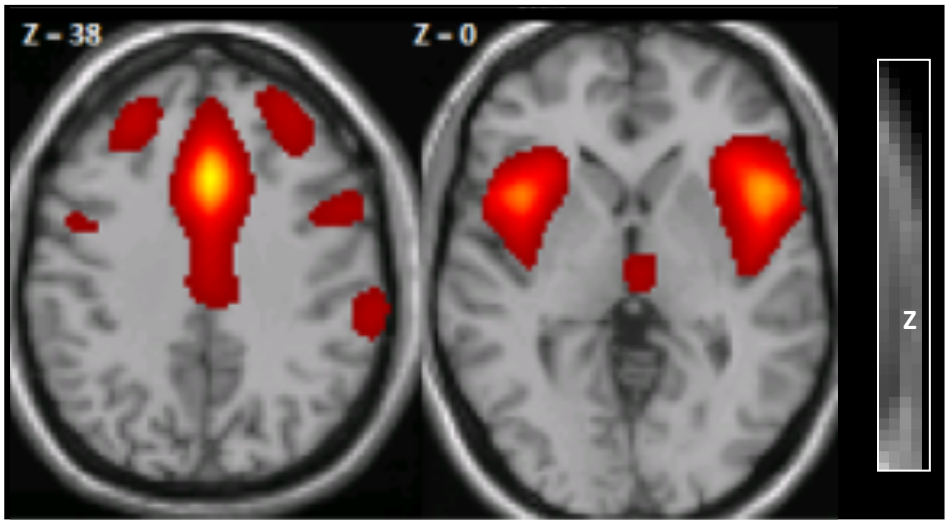

Figure 4. Cinguloinsular network. Spatial correlation with SN template, r = .459, t(40) = 3.29, p < .01. Component maps are visualized with a minimum threshold of z = 1, in standard orientation.

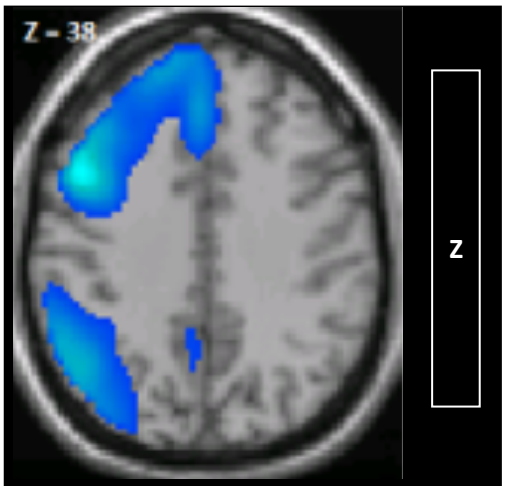

Figure 5. Left frontoparietal network. Spatial correlation with ECN template, r = .325, t(40) = 2.173, p < .05. Component maps are visualized with a minimum threshold of z = 1, in standard orientation.

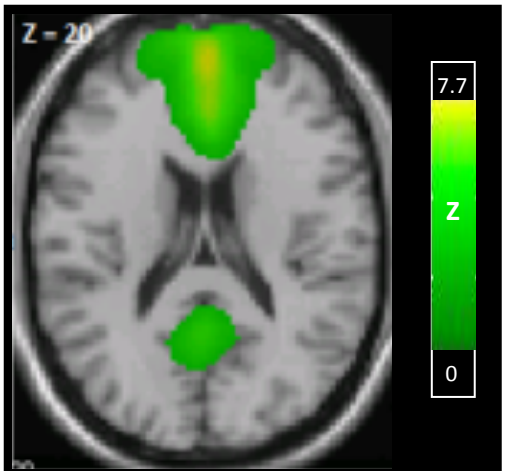

Figure 6. Ventromedial prefrontal network. Correlation with default template, r = .308, $t(40)$ = 2.05, p < .05. Component maps are visualized with a minimum threshold of z = 1, in standard orientation.

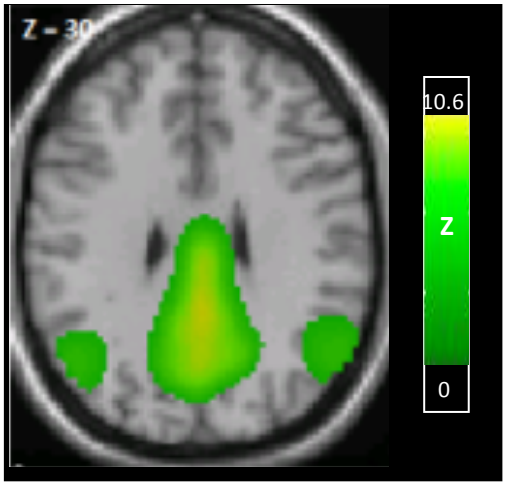

Figure 7. Precuneus network. Correlation with default template: r = .309, $t(40)$ = 2.06, p < .05. Component maps are visualized with a minimum threshold of z = 1, in standard orientation.

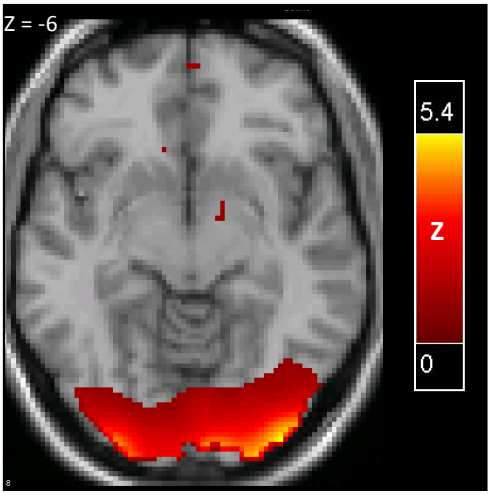

Figure 8. Occipital network - visually selected. Component maps are visualized with a minimum threshold of z = 1, in standard orientation.

3.3 General Linear Model

A 3 Condition x 2 Trial-Type repeated measures ANOVA was conducted on mean betas extracted from a linear regression on the CI network timecourse. The ANOVA yielded a significant interaction that mirrored the conflict adaptation effect in its pattern of betas, F (1,41) = 3.688, p < .05 (see Figure 9). This interaction was characterized by a maximal effect of trial type in the high frequency compatibility condition, with almost no effect of trial type in the low compatibility condition. In this sense, the size congruency effect was largest in the high compatibility condition and decreased as compatibility decreased. The vmPFC network yielded a significant main effect of trial type, demonstrating greater activation in response to compatible, relative to incompatible stimuli, F

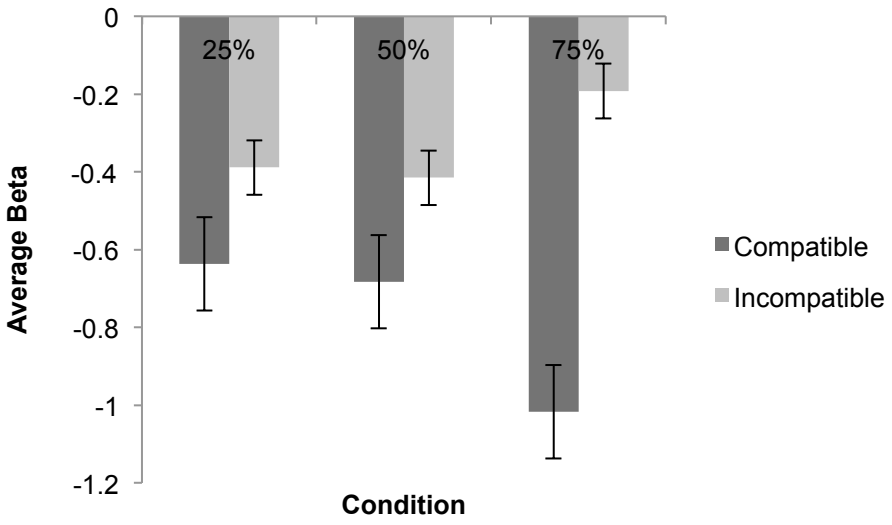

Figure 9. An ANOVA on betas extracted from the CI network yielded a significant interaction, F (1,41) = 3.688, p < .05. This interaction mirrored the CAE, where greatest interference effects were identified in the high compatibility condition, and this effect decreased as the frequency of compatibility decreased.

(1,41) = 7.390, $p < .01$ (see Figure 11). No other significant effects were identified, including in the lFP network (see Figure 10). No other networks yielded significant interaction or main effects.

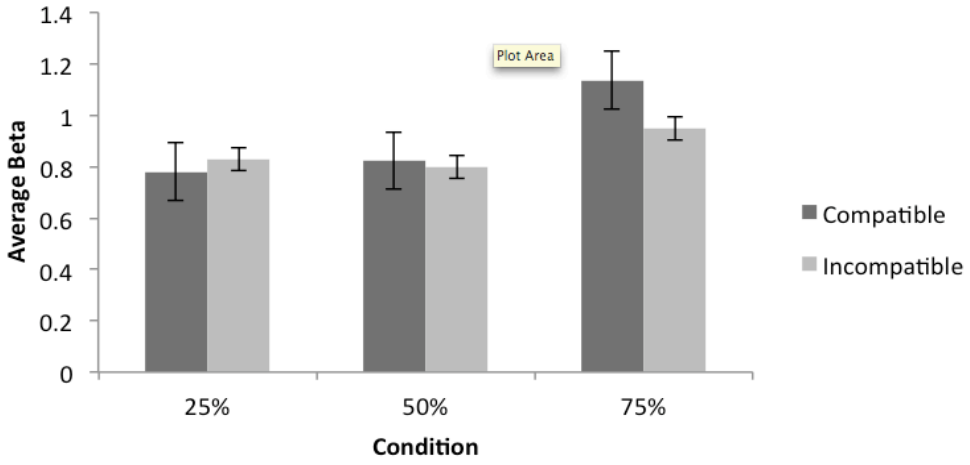

Figure 10. Average betas extracted from the lFP network. An ANOVA on betas yielded no significant effects.

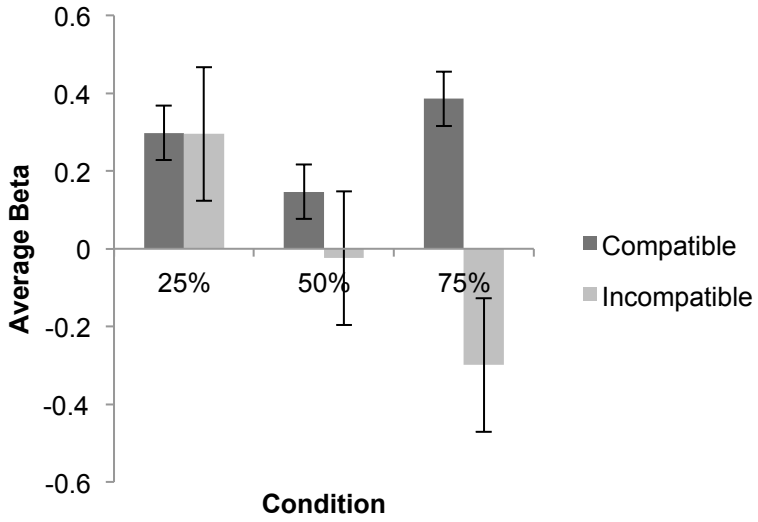

Figure 11. An ANOVA on betas extracted from the ventromedial prefrontal cortex network yielded a main effect of trial-type, F (1,41) = 7.390, $p < .01$. This ANOVA did not yield a significant interaction, F (1,41) = 1.72, *ns*.

3.4 Between-Network Functional Connectivity

Overall between-network FC was identified by calculating Pearson correlation coefficients between the complete timecourses of networks of interest; these correlations have been visualized and enumerated in Figure 12. Timecourses of the lFP network and CI networks were negatively correlated (r = -.4815), $t(40) = -3.475$, $p < .05$. The timecourse of the CI network was negatively correlated with that of both default networks (r_{vmPFC} = -.5488), $t(40) = -4.152$, $p < .0001$, ($r_{precuneus}$ = -.4249), $t(40) = -2.969$, $p < .05$. The timecourse of the lFP network was positively correlated with that of both networks that were selected by the default mode network template (r_{vmPFC} = .6365), $t(40) = 5.219$, $p < .0001$, ($r_{precuneus}$ = .5030), $t(40) = .3681$, $p < .001$. Timecourses of vmPFC and precuneus networks yielded the strongest positive correlation of all comparisons (r = .8220), $t(40) = 9.129$, $p < .0001$.

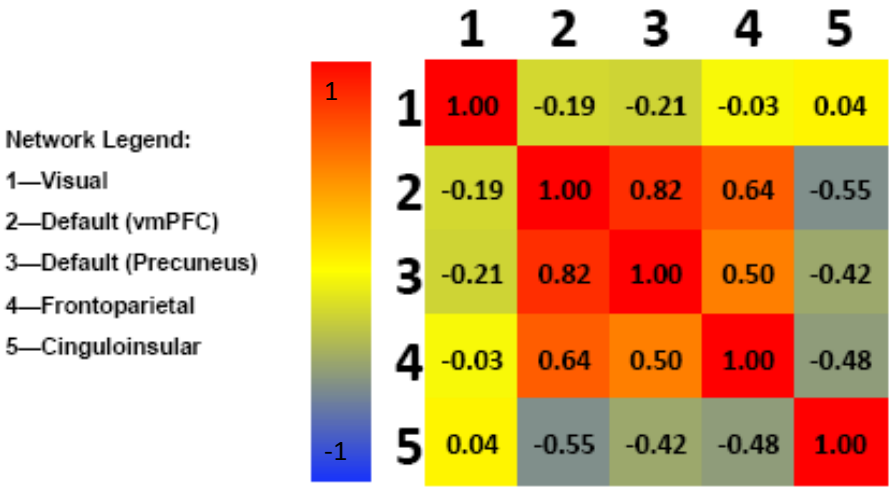

Figure 12. Overall between-network functional connectivity for all networks of interest. Pearson correlation coefficients calculated based on correlation of timecourses between all networks of interest are enumerated and visualized in this correlation matrix. All network pairings can be identified using the network legend, and labels on the x and y axes. Colour visualizations of Pearson correlation coefficients range from blue (perfect negative correlation) to yellow (no correlation) to red (perfect positive correlation).

3.5 Condition Induced Fluctuations of Between-Network Functional Connectivity

The pattern of correlations identified above remained relatively stable when investigated in isolated condition windows (see Figure 13).

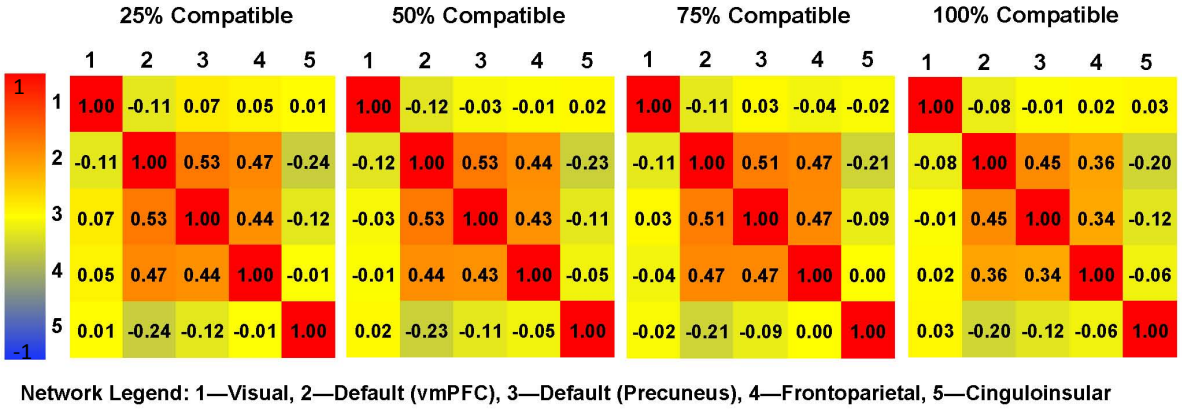

Figure 13. Condition specific between-network functionally connectivity for all networks of interest. Pearson correlation coefficients were calculated based on correlation of timecourses extracted from specific condition windows; comparisons between all networks of interest are enumerated and visualized in these correlation matrices. All network pairings can be identified using the network legend, and labels on the x and y axes. Colour visualizations of Pearson correlation coefficients range from blue (perfect negative correlation) to yellow (no correlation) to red (perfect positive correlation). Each correlation matrix is specific to a particular condition, as indicated by matrix titles.

Chapter 4 – Discussion

4.1 Preamble

Resting state fMRI data has become widely used to assess FC. This has been a promising area of research, and has enabled the identification of, as well as spatial and architectural characterization of functional networks in the brain through a variety of analytical approaches (Dosenbach et al., 2007, 2008; Seeley et al., 2007; Cole & Schneider, 2007). However, without an ability to directly assess BOLD modulation in the context of a task performed online, it has been difficult to consistently functionally characterize the networks under discussion. This issue calls for the use of analytical tools for assessing functional networks in event-related fMRI data.

4.2 ICA as a tool to identify functional networks in event-related fMRI

Twenty stable functional networks were identified from a spatial ICA conducted on event-related fMRI data. These networks were consistently extracted from the data over 100 iterations of the analysis, starting with random initial weightings in each iteration. The networks also appeared spatially consistent with functional networks discussed in the resting state literature upon visual inspection. The networks extracted consisted of spatial topographies that have typically been identified as frontoparietal, cinguloinsular, default mode, visual, and motor, among others. Furthermore, networks of interest were selected using spatial correlation with templates from the resting state literature

(Seeley et al., 2007 and Bluhm et al., 2008). The network that demonstrated the highest spatial correlation with each template was selected. Selecting components based on spatial correlation with templates from the resting state literature allowed us to objectively select components of interest based on *a priori* hypotheses.

The ability to extract consistent networks from both resting state and event-related fMRI data using ICA is a strong indicator of the robustness of this analytical tool, which has been demonstrated in other studies (Calhoun et al., 2008). This indicates the effectiveness of ICA in moving toward functionally characterizing cortical networks. Aside from extracting networks spatially consistent with those discussed in the resting state literature, ICA offers several other benefits. First, extracted networks include a timecourse that can be used to identify BOLD modulation of the network during a task in a standard GLM. This is arguably a more direct way to identify whether, and how functional networks are involved in specific cognitive tasks. Second, since ICA extracts maximally independent sources of spatial variance from fMRI data, sources of artifacts such as cardiac rhythms and motion are assigned to their own components; this leaves components of interest relatively free from artifactual sources of variance (Calhoun & Adali, 2006; Himberg et al., 2004). Furthermore, the spatial characterization of our networks takes into account variance from voxels in the whole-brain, avoiding potential biases of FC scores based on *a priori* seed selection. These factors made ICA an effective tool for the identification and

objective selection of functional networks that could subsequently be functionally characterized.

4.3 Network Selection

CI and lFP networks were selected based on spatial correlations with SN and ECN templates, respectively (Seeley et al., 2007). The lFP network primarily consisted of lateral prefrontal cortex and PPC. It was reminiscent of the adult FP network investigated using graph theoretic approaches (Dosenbach et al., 2007, 2008) as well. The CI network extracted included the ACC, AI, and FO. The spatial architecture of this network is characteristic of the CP network discussed in Dosenbach et al. (2007, 2008). Two networks were selected from correlation with a default mode network template (Bluhm et al., 2008). One network consisted primarily of vmPFC and another primarily of the precuneus. Together, these networks form a typical spatial profile of default networks that have been discussed in the resting state fMRI literature.

A robust occipital network was chosen as a control network based on visual inspection. This network was included to ensure that effects seen in the functional analysis of our networks were specific to those which comprised regions that have been implicated in control.

4.3 Functional characterization of the CI network

It was hypothesized that the CI network would demonstrate a pattern of betas consistent with the CAE. This prediction was based on the characterization of this network as a salience network (Seeley et al., 2007; Menon & Uddin, 2010). The salience network has been said to 'flag' salient events that are relevant to a particular task or behavior for further processing. According to this characterization, the CI network should engage in bottom-up processes related to identifying relevant information during and engaging the relevant control processes necessary to inform and appropriate response (Menon & Uddin, 2010). These processes become most relevant in the high compatibility condition of our hybrid task, informing our hypothesis that a pattern of betas extracted from the CI network would yield a CAE. This pattern manifested in our data. A typical CAE was elicited in the pattern of betas of the CI network; this pattern involved greater interference effects in the high compatibility condition relative to the medium and low compatibility conditions. Thus, this network demonstrates greater modulation in response to conflict that is more salient, or less predictable based on the statistical environment. This characterization is not consistent with the idea that the CP network (Dosenbach et al., 2007, 2008) is implicated in stable task-set maintenance. Representations of the task-set are weakest in the high compatibility condition of this task, while demands on moment-to-moment adjustments in control are strongest (Wilk et al., 2012). The BOLD signal in the CI network was most strongly modulated during the high compatibility condition, implicating its involvement in processing moment-to-moment adjustments in

control. This finding is consistent with findings from our voxel-wise GLM analysis, where ACC and AI were identified by a predictor that probed moment-to-moment adjustments in control (Wilk et al., 2012).

These findings indicate several characteristics associated with cortical regions involved in the CI network. First, it appears that regions of the ACC, AI, FO, thalamus, and limbic structures function as a functionally integrated network in the context of Executive Control Tasks. Second, these regions appear to be involved in the processing of moment-to-moment adjustments in control; they are related to processing unpredictable conflict that is statistically infrequent in the context. Third, these regions appear to operate independently from other areas, specifically FP areas, that have been previously associated as part of an integrated CCN (Cole & Schneider, 2007).

4.4 Functional characterization of the lFP network

FP regions have often been implicated in executive control tasks (Wilk et al., 2012, Cole & Schneider 2007). The FP network has been characterized as an executive control network based on the correlation between connectivity in this network and offline executive control tasks (Seeley et al., 2007). It has also been proposed that this network is involved in moment-to-moment adjustments in control (Dosenbach et al., 2007, 2008). In this GLM, an ANOVA on betas extracted from the lFP network yielded no significant effects. Based on previous implications of this network in executive control, it was hypothesized that it would yield a significant conflict effect. Furthermore, according to the Dosenbach et al.

(2007, 2008) account, it would have yielded a pattern of betas reminiscent of the CAE, as was identified in the CI network. That the lFP network yielded no significant effect in this GLM appears to indicate that it is not involved in moment-to-moment adjustments in control as they are measured by this task. However, with extant evidence strongly indicating this network's involvement in executive control, this could be related to the type of analysis and scale of networks under investigation in this study. Frontoparietal regions are distal cortical regions connected by long-range white matter connections (Eickhoff et al., 2010). While they are strongly functionally connected, it is feasible that they are involved in different executive control processes that are related but dissociable; this could lead to challenges in identifying BOLD modulation across the whole network during task performance. Both dlPFC and PPC appear to be involved in this task (Wilk et al., 2012), however, this effect does not appear to be detectable when investigating how these regions function as a whole unit.

4.5 Functional characterization of the vmPFC default network

The vmPFC network extracted from a default mode template (Bluhm et al., 2008) yielded a significant main effect of trial type, but no significant interaction. Previous studies assessing default network BOLD modulation during executive control tasks have indicated that the network, particularly the vmPFC node, can be modulated by cognitively demanding tasks (Sridharan, Levitin & Menon, 2008; McKiernan et al., 2003). This network demonstrated greater activation for compatible stimuli relative to incompatible stimuli, the opposite modulation

typically identified in task-active networks. This finding is consistent with evidence in the cognitive control literature that indicates deactivation in this network in the face of cognitively demanding tasks, and activation of this network at rest (Sridharan, Levitin & Menon, 2008; Hasson et al., 2009; McKiernan et al., 2003).

4.6 Between-network FC

As anticipated, timecourses of the CI and lFP networks were significantly correlated. However, this was a negative correlation, which appeared to be driven by strong stimulus-induced negativities in the timecourse of the CI network. The negative post-stimulus deflection in the CI timecourse was explored at length, and it appeared to be a consistent finding that drove both the negative betas identified in our functional analysis, and negative correlations between the CI network and other networks under investigation. However, since this timecourse is back-reconstructed from variance across a large number of voxels involved in the component, the valence of network BOLD signals associated with independent components can be more challenging to interpret relative to that of a single voxel or ROI. Subsequently, patterns of modulation and correlation become the focus of ongoing analyses, rather than the valence of these relationships.

The CI network timecourse was significantly negatively correlated with both default network timecourses. This pattern is relatively typical of other findings in the cognitive control literature. Typically, default regions are

deactivated to the degree that individuals are engaged in cognitively effortful tasks (Sridharan, Levitin & Menon, 2008; Hasson et al., 2009; McKiernan et al., 2003); thus, one might expect that conflict processing in a high compatibility condition, and subsequent modulation of the CI network would be negatively related to modulation of the default networks.

vmPFC and precuneus default networks demonstrated the strongest positive correlation identified out of all our between-network correlations. These regions are often clustered within a unified default mode network (Bluhm et al., 2008); the strong positive correlation between these regions is highly consistent with the default network literature and indicates that despite being unmixed in this ICA, these components often operate in unison.

4.7 Condition-specific between-network functional connectivity

The pattern of between-network correlations was quite consistent across different conditions. Several factors likely underlie the consistency identified in functional connectivity across conditions. First, the difference between conditions in this task is relatively subtle. While differences in the statistical environment of compatibility in a number comparison task influences conflict processing, participants were viewing the same type of stimuli and performing very similar motor, and cognitive operations aside from disentangling conflict. It is conceivable that more drastic contrasts in task conditions would be necessary to stimulate differences in FC between large-scale functional networks. Second, the time windows from which condition-specific FC correlation coefficients were

calculated were substantially shorter than time windows used to measure overall between-network FC. This likely explains the reduction in between-network FC in the condition specific analysis, relative to the overall between-network FC analysis. The reduction of power in this analysis might also have mitigated our ability to identify subtle differences in FC patterns in different conditions. Third, the scale of these networks is quite expansive. Our analysis was conducted with a relatively low model order; therefore, large scale networks were extracted that were comparable to those discussed in the resting state literature. The scale of the networks likely diluted our ability to identify condition specific changes in functional connectivity, which could be specific to smaller cortical regions.

4.8 Limitations and Future Directions

ICA is a promising tool for studying the structure and function of cortical networks using fMRI. However, the scale of networks extracted in this study limited subsequent analysis on timecourses in the GLM analysis, and between-network FC analysis. A low model order was chosen, extracting only 20 components from the raw data to ensure that the networks extracted from our event-related data were comparable in scale to those extracted from resting state data in the literature (Seeley et al., 2007, Dosenbach et al., 2007, 2008). However, this reduced the comparability between our GLM findings and findings from ROI or whole-brain GLM analyses. Timecourses in this analysis were based on raw data from a large number of voxels. This was beneficial in the sense that a whole network could be functionally characterized based on its timecourse;

however, our ability to draw reference to previous findings from the fMRI literature was reduced by the scale of these networks. Furthermore, the same issue impacted our between-network FC analysis, particularly the analysis of condition specific between-network FC. As mentioned, the scale of the networks likely diluted subtle, region specific differences in FC that might have been identified in smaller-scale networks.

Two approaches could mitigate some of these issues in follow-up analyses. First, a high model order could be specified in the initial ICA, to extract more functional networks that are of smaller scale from the raw data. It would be then be possible to identify the smaller networks that were absorbed into a single CI or IFP network in this analysis; these ‘subnetworks’ could be identified using spatial correlation with CI and IFP templates generated in this study. A second alternative involves using the CI or IFP networks generated in this analysis as a mask in an ICA analysis to identify smaller functional networks within each of these large-scale networks. If small-scale networks were identified by either of these approaches, GLM and between-network FC analyses could be conducted with greater efficacy and sensitivity.

Chapter 5 – Summary and Conclusions

This study is unique in its attempt to functionally characterize large-scale networks by modeling variance in their activity timecourses. The robustness of ICA was replicated, as well as its ability to identify consistent functional networks in both resting and event-related fMRI data. Using a spatial selection criterion, components were objectively extracted from an ICA on event-related fMRI data that were spatially correlated with those identified in resting state FC analyses. ICA is unique among tools for assessing FC, in that networks identified are associated with a timecourse. This enabled a direct assessment of BOLD modulation in these functional networks during specific aspects of a cognitive control task. Effects that implicated a CI network in moment-to-moment control processing were identified, consistent with the characterization of this network as a salience network. Timecourses associated with functional networks in this study also enabled a between-network FC analysis; however, the scale of networks under investigation limited our ability to identify condition specific changes in FC. ICA offers promising solutions to this issue that can be implemented in future studies.

Overall, this study emphasized the benefits of and potential to studying networks as functionally cohesive units, rather than distributed regions. It also demonstrated the ability to identify dissociations in network function using a task that independently probes specific cognitive demands in a single task. With ongoing research, it will be possible to identify executive control processing

across integrated functional networks, and understand how each network is related to specific control processes.

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Appendix 1 – Ethics Approval

Office of Research Ethics

The University of Western Ontario
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Use of Human Subjects - Ethics Approval Notice

Principal Investigator: Dr. J.B. Morton
Review Number: 15411 **Review Level:** Full Board
Review Date: August 12, 2008
Protocol Title: Developmental changes in brain networks that subserve executive control
Department and Institution: Psychology, University of Western Ontario
Sponsor: NSERC-NATURAL SCIENCES ENGINEERING RSRCH COU
Ethics Approval Date: September 17, 2008 **Expiry Date:** September 30, 2010
Documents Reviewed and Approved: UWO Protocol, Letter of Information and Consent, Assent Letter, Advertisement, Telephone Script.
Documents Received for Information:

This is to notify you that The University of Western Ontario Research Ethics Board for Health Sciences Research Involving Human Subjects (HSREB) which is organized and operates according to the Tri-Council Policy Statement: Ethical Conduct of Research Involving Humans and the Health Canada/ICH Good Clinical Practice Practices: Consolidated Guidelines; and the applicable laws and regulations of Ontario has reviewed and granted approval to the above referenced study on the approval date noted above. The membership of this REB also complies with the membership requirements for REB's as defined in Division 5 of the Food and Drug Regulations.

The ethics approval for this study shall remain valid until the expiry date noted above assuming timely and acceptable responses to the HSREB's periodic requests for surveillance and monitoring information. If you require an updated approval notice prior to that time you must request it using the UWO Updated Approval Request Form.

During the course of the research, no deviations from, or changes to, the protocol or consent form may be initiated without prior written approval from the HSREB except when necessary to eliminate immediate hazards to the subject or when the change(s) involve only logistical or administrative aspects of the study (e.g. change of monitor, telephone number). Expedited review of minor change(s) in ongoing studies will be considered. Subjects must receive a copy of the signed information/consent documentation.

Investigators must promptly also report to the HSREB:

a) changes increasing the risk to the participant(s) and/or affecting significantly the conduct of the study;
b) all adverse and unexpected experiences or events that are both serious and unexpected;
c) new information that may adversely affect the safety of the subjects or the conduct of the study.

If these changes/adverse events require a change to the information/consent documentation, and/or recruitment advertisement, the newly revised information/consent documentation, and/or advertisement, must be submitted to this office for approval.

Members of the HSREB who are named as investigators in research studies, or declare a conflict of interest, do not participate in discussion related to, nor vote on, such studies when they are presented to the HSREB.

Chair of HSREB: Dr. Joseph Gilbert

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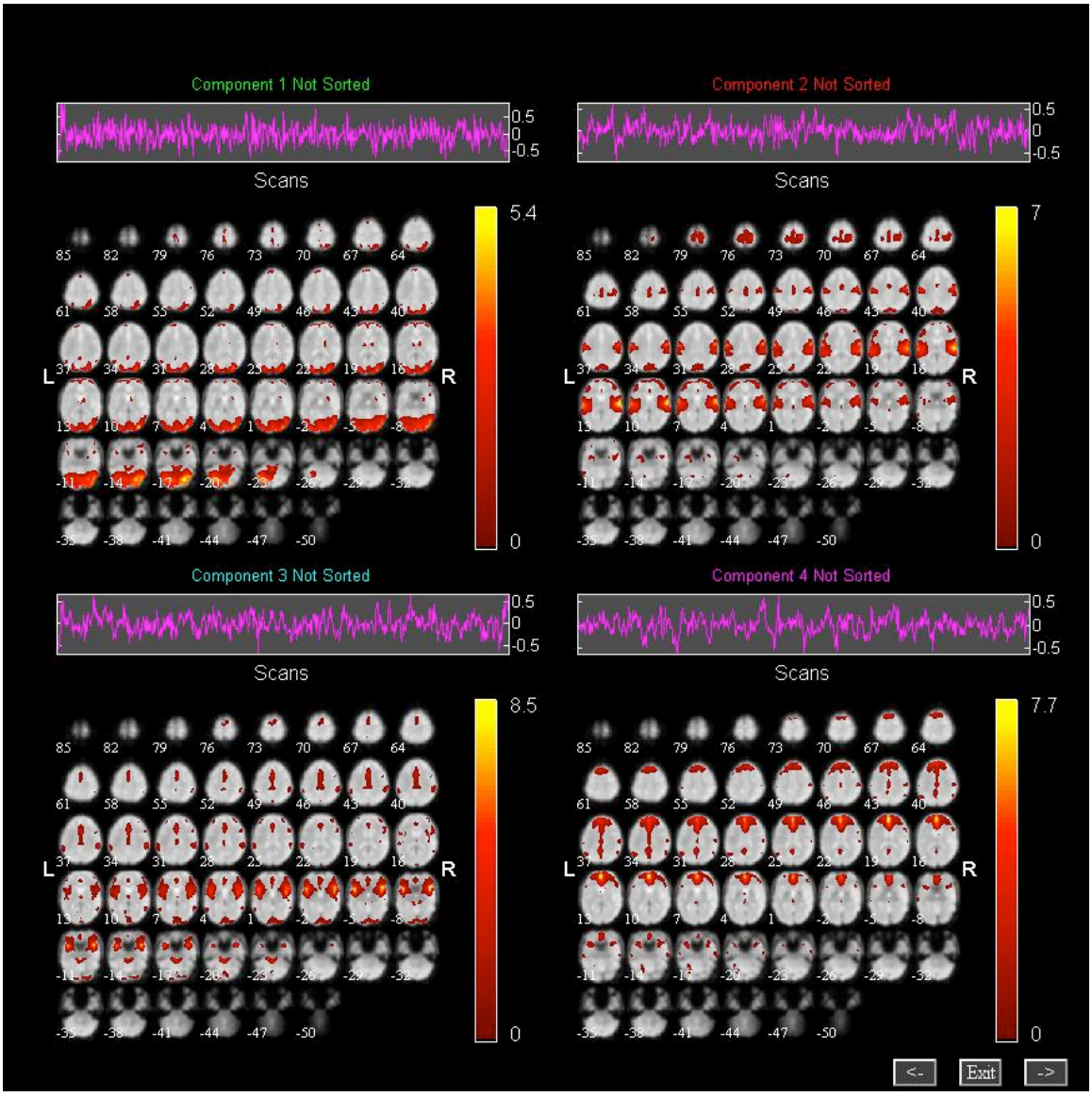
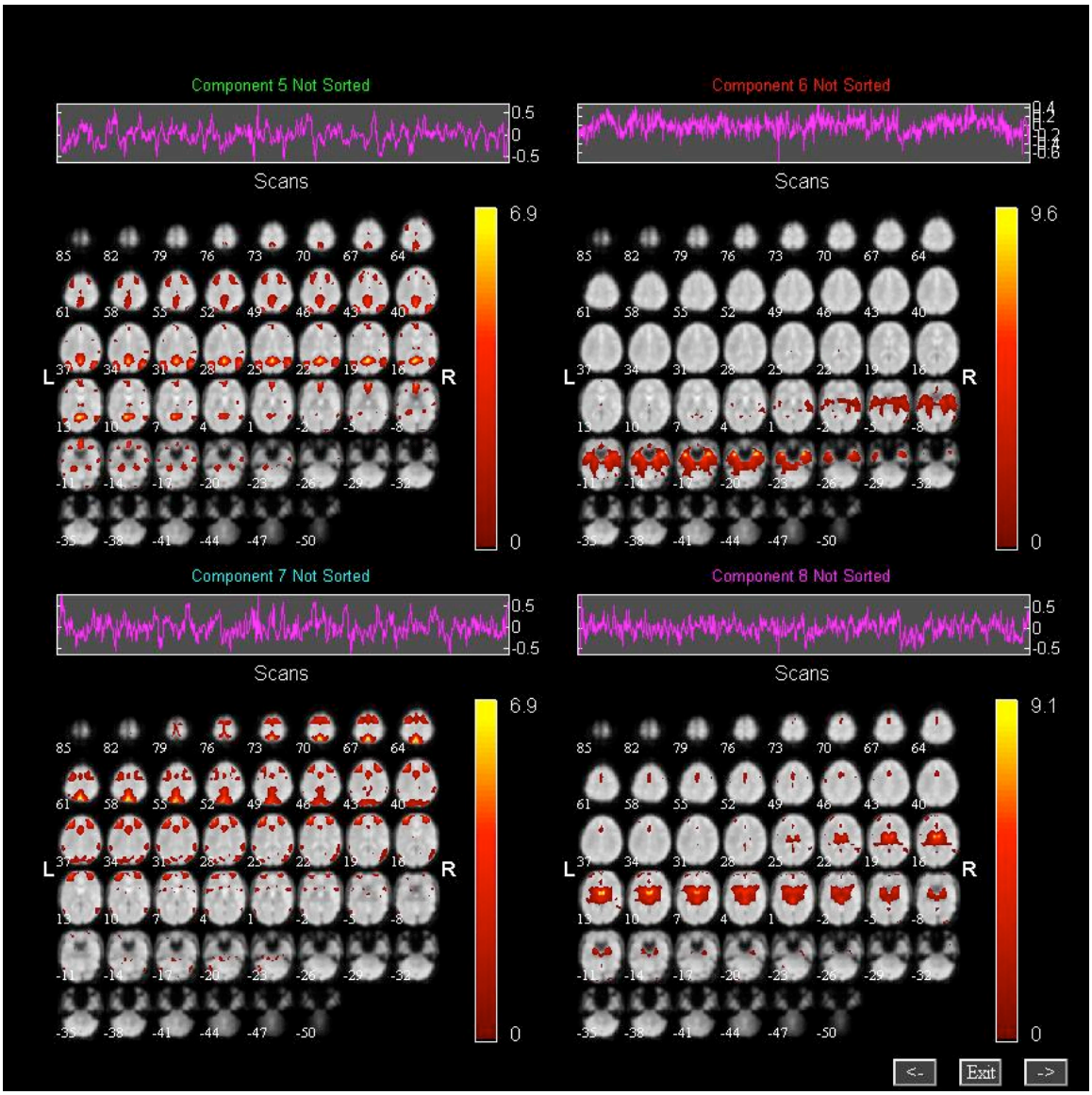
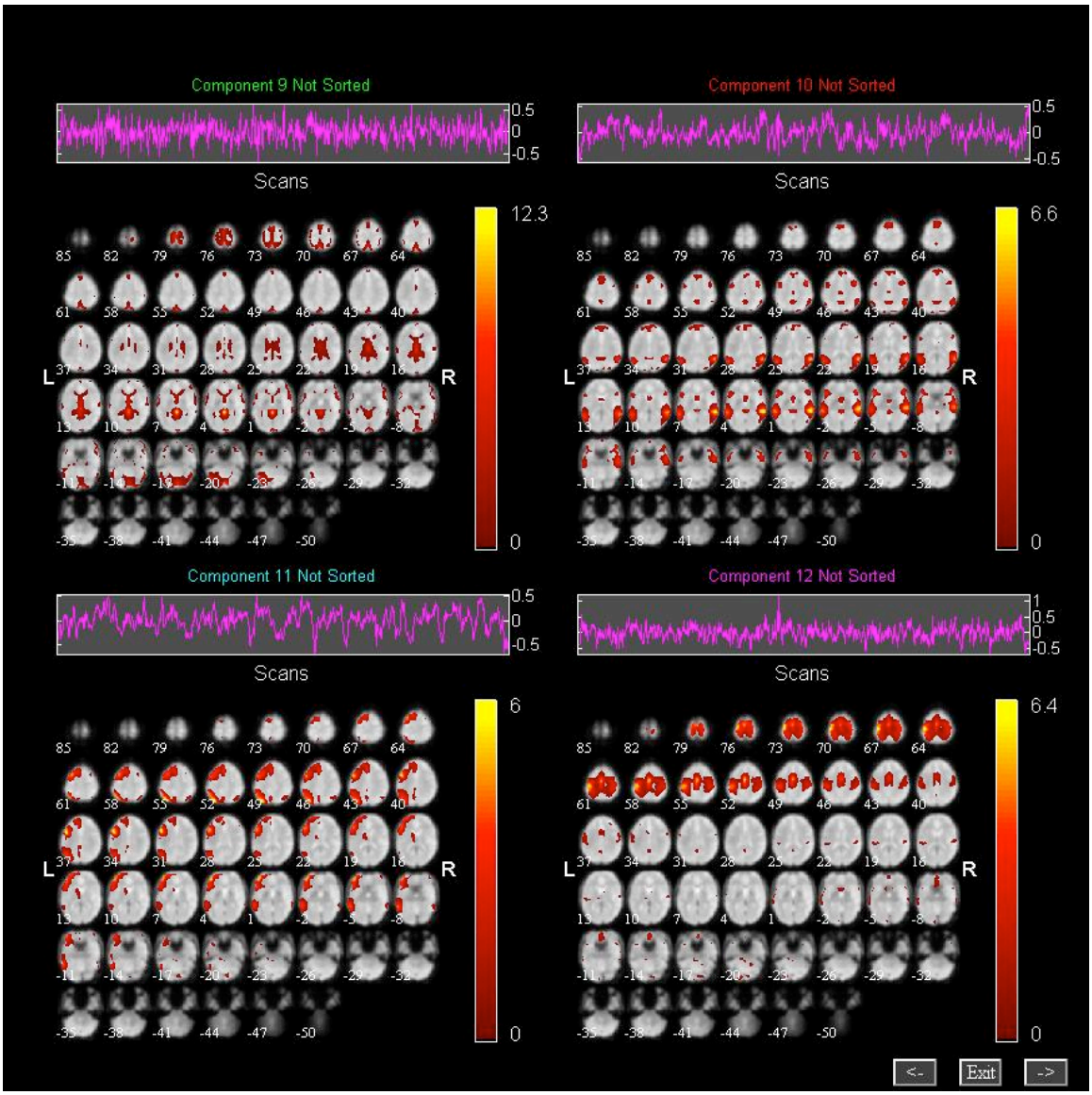
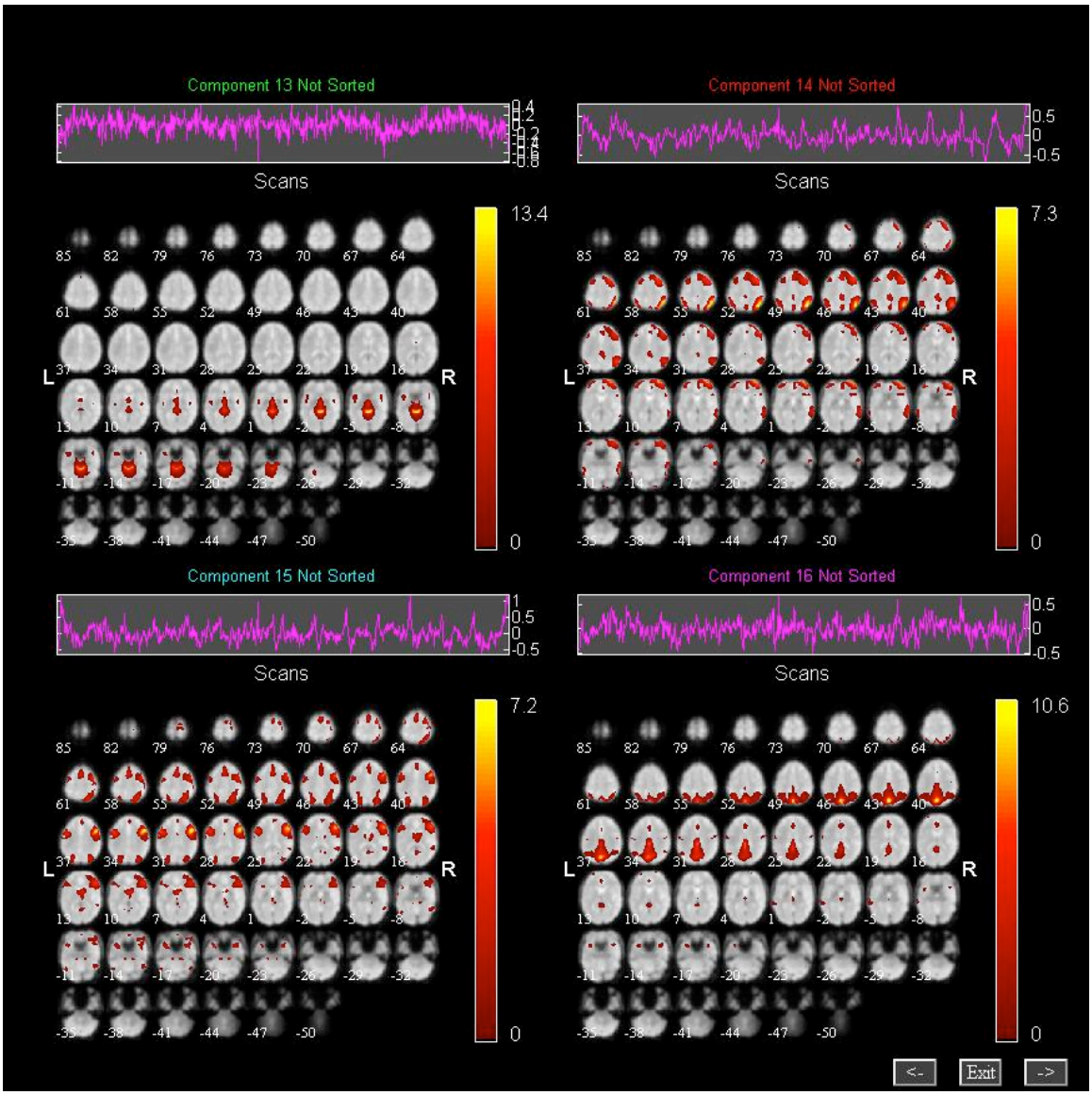
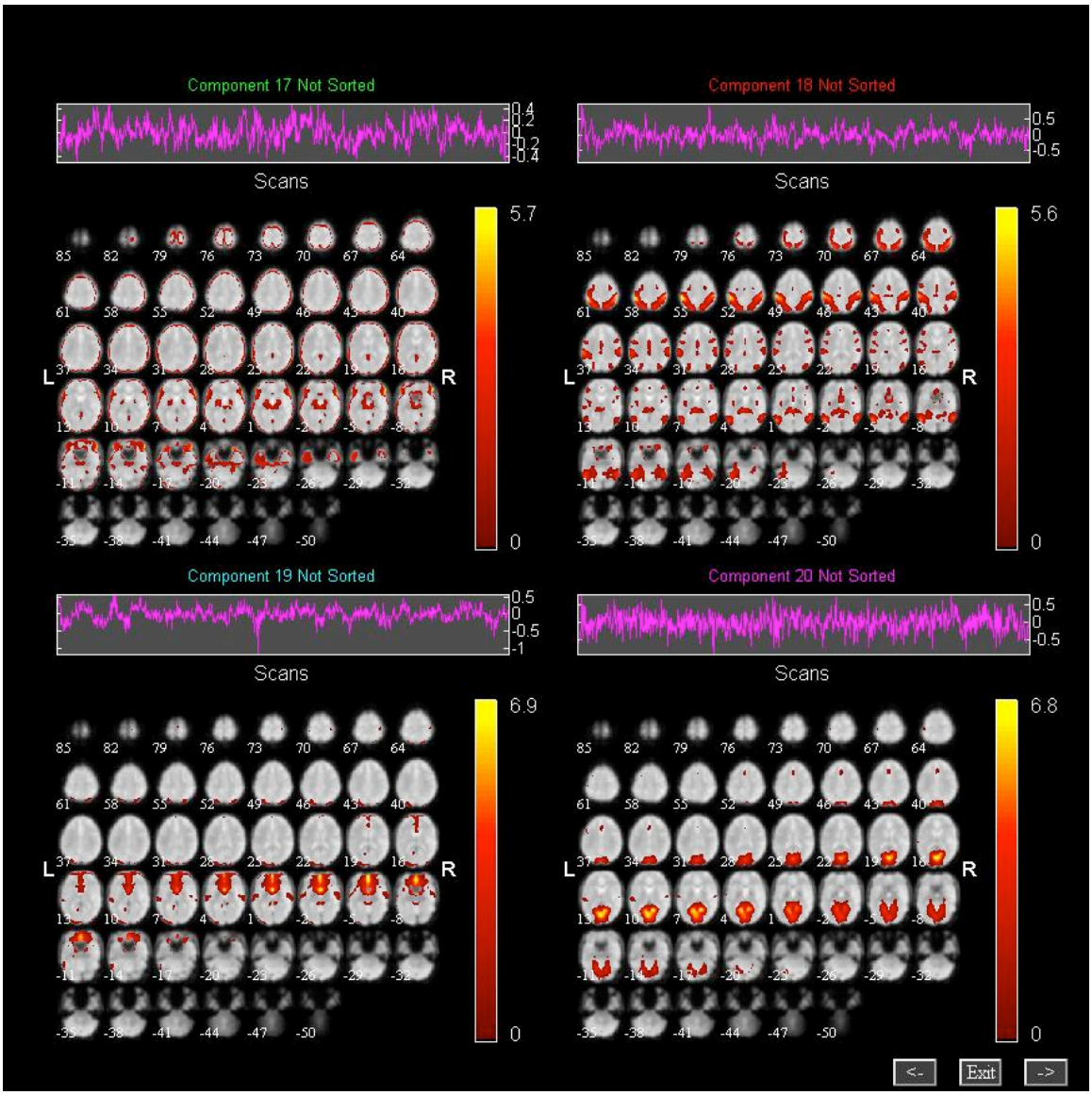
Appendix 2 – Extracted Independent Components




Component 5 Not Sorted
Scans
Component 6 Not Sorted
Scans
Component 7 Not Sorted
Scans
Component 8 Not Sorted
Scans
L
R
<-
Exit
->


Component 9 Not Sorted
0.5
0
-0.5
Scans
12.3
0
Component 10 Not Sorted
0.5
0
-0.5
Scans
6.6
0
Component 11 Not Sorted
0.5
0
-0.5
Scans
6
0
Component 12 Not Sorted
1
0.5
0
-0.5
Scans
6.4
0
L
R
<-
Exit
->


Component 13 Not Sorted
Scans
13.4
0
Component 14 Not Sorted
Scans
7.3
0
Component 15 Not Sorted
Scans
7.2
0
Component 16 Not Sorted
Scans
10.6
0
L
R
<-
Exit
->


Component 17 Not Sorted
Scans
Component 18 Not Sorted
Scans
Component 19 Not Sorted
Scans
Component 20 Not Sorted
Scans
L
R
<-
Exit
->

FREDERICK EZEKIEL

EDUCATION

M.Sc. Candidate – 2012, Neuroscience, Schulich School of Medicine and Dentistry

University of Western Ontario, London, Ontario [9/2010 - Present]

- Thesis Topic: Toward a functional characterization of cognitive control networks.

Bachelor of Arts - Psychology

University of Western Ontario, London, Ontario [9/2006 – 4/2010]

- Independent research topic: Functional connectivity of brain networks involved in card sorting.
- Dean's Honour List: 06/07, 09/10

ACADEMIC AWARDS AND DISTINCTIONS

- **Western Graduate Scholarship** - ($9,100 – 2010/2011, $9,100 – 2011-2012)
- **Pepsico Excel Merit Scholarship** - ($25,000 – 2006-2010)
- **Robert and Ruth Lumsden Undergraduate Award in Science** - ($1,000 – 2006/2007)
- **Government of Canada: Millenium Scholarship of Excellence** - ($4,000 – 2006/2007)
- **Western Scholarship of Excellence** - ($2,000 – 2006/2007)

RESEARCH INTERESTS

My research focuses on using multivariate approaches to investigate functional and structural connectivity in the human brain. I apply independent component analysis (ICA) to fMRI data to investigate brain networks involved in executive functioning tasks, both functionally and structurally. My research fits into a larger laboratory context of investigating the development of cortical regions involved in cognitive control from childhood into adulthood.

PUBLICATIONS

- **Ezekiel, F.**, & Morton, J.B. (Submitted). Dimensional Shifts of Attention Reveal Age-related Changes in Functional Connectivity in a Cognitive Control Network. *Developmental Cognitive Neuroscience.*
- Wilk, H., **Ezekiel, F.** & Morton, J.B. (In Press). Brain Regions Associated with Moment-to-Moment Adjustments in Control and Stable Task-Set Maintenance. *Neuroimage*.
- Morton, J.B., **Ezekiel, F.** & Wilk, H. (In Press). Executive functioning: easy to identify, hard to define. *Topics in Cognitive Science*.

- Contributing Author. First Year University: A Survival Guide. Editors: Young, D & Gray, N. Toronto: CSSP, 2011.

PRESENTATIONS AT PROFESSIONAL MEETINGS

- **Ezekiel, F.** & Morton, J.B. (June 2011). Toward a functional characterization of cognitive control networks. Poster – 17th Annual Meeting of the Organization for Human Brain Mapping, Quebec City, Canada, June 2011.
- **Ezekiel, F.** & Morton, J.B. (April 2011). Developmental Changes in Brain Networks Involved in Dimensional Shifts of Attention. Poster – Biennial Meeting of the Society for Research in Child Development, Montreal, Canada.
- **Ezekiel, F.** & Morton, J.B. (June 2010). Independent functional components associated with dimensional shifts of attention. Poster – 16th Annual Meeting of the Organization for Human Brain Mapping, Barcelona, Spain.
- Morton, J.B., **Ezekiel, F.** & Wilk, H. (June 2010). Dual networks supporting conflict processing: an fMRI study of conflict adaptation effects. Poster - 16th Annual Meeting of the Organization for Human Brain Mapping, Barcelona, Spain.

TEACHING EXPERIENCE

Teaching Assistant, University of Western Ontario – [9/2010 – Present]
Psychology 3485F [Fall 2010] – Research in Developmental Cognitive Neuroscience

- Taught weekly lab sessions focusing on the practical aspects of conducting fMRI and ERP research.

Psychology 3441G [Winter 2011] – Frontal Cortex and the Development of Cognitive Control

- Responsible for responding to student questions, conducting review sessions, and marking students' assignments and exams.

CONFERENCES & TRAINING

Student Affairs Administrators in Higher Education – Phoenix, United States [3/2012]

Organization for Human Brain Mapping – Quebec, Canada [6/2011]

Society for Research in Child Development – Montreal, Canada [4/2011]

Organization for Human Brain Mapping – Barcelona, Spain [6/2010]

Lake Ontario Visionary Establishment – Niagara Falls, Canada [2/2010 & 2/2011]

National Orientation Directors Association (NODA) – Waterloo, Ontario [4/2008]

Queen's National Undergraduate Conference on Medicine – Queen's University, Kingston, Ontario [10/2007]

Youth Advocacy Training Institute (YATI), 1st Annual Take Action Conference – Toronto, Ontario [3/06]

LEADERSHIP EXPERIENCE, ADMINISTRATIVE POSITIONS AND COMMUNITY INVOLVEMENT

Student Success Centre, University of Western Ontario

Professional Experience

- **Coordinator of Student Engagement Programs** – [7/2011 – Present]
  - Enabled leadership development opportunities for 2351 Western undergraduate students in 140 different workshops themed around 14 specific leadership skills through Western's Leadership Education Program.
  - Facilitated service learning experiences for 150 students in 7 countries over reading week through Western's Alternative Spring Break Program.
  - Fostered a sense of community that encouraged personal and academic success, and civic engagement for 950 first year students registered in the Society of Off-Campus Students (SOCS). Supervised 57 upper-year student leaders who facilitated the day-to-day operations of SOCS.
- **Academic Advisor – Summer Academic Orientation Program** - [6/2011 – 7/2011]
  - Advised incoming first-year undergraduate students regarding their first year course selection and module progression for upper years at Western.

Student Leadership Experience

- **Leadership Education Program (LEP) Facilitator** - [9/2010-4/2011]
- **Leadership and Mentorship Program (LAMP) Co-Student Coordinator** - [9/2006 – 4/2010]
- **Western Serves (service learning program) Coordinator**- [4/2008 – 9/2008]
- **Western Community Service Learning Network (CSLN) Co-Founder** [9/2009]
- **Summer Academic Orientation (SAO) Leader** [2008, 2009]

UWO Red Cross Society, London, Ontario

- **Co-President** [08/09]
- **VP Marketing** [07/08]

Community Events:

- **RONA MS Bike Tour** – Grand Bend to London, Ontario – [7/2010 & 7/2011]
- **Elizabeth Reurink Memorial Run (Anti-Bullying Coalition)** – London, Ontario – [2010]
- **London Health Sciences Centre Run for Ovarian Cancer** – London, Ontario – [2009 & 2010]
- **Terry Fox Run –** London, Ontario [2006, 2007 & 2008]

LEADERSHIP AWARDS AND DISTINCTIONS

- **Student Success Centre Award of Excellence –** [2009-2010]

- **University of Western Ontario Excellence in Leadership Award: Gold** – [2007-2008, 2008-2009]