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The Influence of Spatial Smoothing Kernel Size on the Temporal Features of Intrinsic Connectivity Networks

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***Abstract*— Spatial smoothing is a common preprocessing step in the analysis of functional magnetic resonance imaging (fMRI) data. However, little is known about the effect of spatial smoothing kernel size on the temporal properties of functional brain networks. This study presents a pilot investigation on the influence of spatial smoothing using independent component analysis (ICA) as a data-driven technique to extract functional networks of brain in the form of intrinsic connectivity networks (ICNs). BOLD resting state fMRI data were collected from 22 healthy subjects on a 3.0 T MRI scanner. 3D spatial smoothing was applied using a Gaussian filter with full width at half maximum (FWHM) kernel sizes of 4 mm, 8 mm, and 12 mm in the preprocessing step. Group ICA with the Infomax algorithm was performed at 75-IC decomposition. Network temporal features including functional network connectivity (FNC) and BOLD power spectra were calculated and compared pairwise using a paired *t*-test with a false discovery rate (FDR) correction for multiple comparisons. Results revealed robust effects of smoothing kernel size on FNC measures of most ICNs, largely indicating a decrease in inter-network connectivity as the smoothing kernel size decreased. Power spectra analysis showed increased high-frequency power (0.15 – 0.25 Hz) but decreased low-frequency power (0.01 – 0.10 Hz) with a decrease in the smoothing kernel size (corrected $p < 0.01$). These findings provide a preliminary observation on the effect of spatial smoothing kernel size on the FNC and power spectra.**

I. INTRODUCTION

Functional magnetic resonance imaging (fMRI) represents a powerful, non-invasive tool that can assist in investigating the functioning of the brain. It indirectly measures neural activity predominantly by the blood oxygenation level-dependent (BOLD) effect among others. However, due to the nature of BOLD signals and the inherent presence of different artifacts, acquired images generally require some types of preprocessing before meaningful statistical inferences of neural processes are made [1]. Spatial smoothing is a typical preprocessing step with a standard procedure involving a convolving of the BOLD signals with a Gaussian function of a specific width expressed in terms of the Full Width at Half Maximum (FWHM) [1]. The primary benefits of applying spatial smoothing are to improve the signal to noise ratio (SNR) by suppressing the spatial noise. But there are also drawbacks when using inappropriate smoothing kernel size such as reduced spatial resolution and specificity. There is no consensus on the kernel size. Previous studies suggested that the smoothing FWHM should be at least twice the size of the acquired voxel size (i.e., smoothing kernel S = 6 or 8 mm for a typical voxel size of approximately 3-4 mm), while other advocated different kernel sizes ranging from 4 to 12 mm depending on the nature of the data (resting state vs. task activation fMRI), and analysis approach (univariate vs. multivariate) [2]–[4].

Previous research showed that large smoothing kernel may cause a correlation-based functional overestimation [5]. In a regression-based analysis study, spatial smoothing was found to have an inverse effect on functional connectivity thereby suggesting a dependency of functional connectivity on different smoothing kernels [6]. A more recent study examined the spatial smoothing effects on independent component analysis (ICA)-based task fMRI data and found an increase in the functional coupling strengths with spatial smoothing [7]. Up to the present, the influence of spatial smoothing on temporal features of ICA-derived intrinsic connectivity networks (ICNs) have not been rigorously investigated especially in resting state BOLD fMRI data. This study aims to investigate the effects of spatial smoothing kernel size on ICNs by focusing on the (1) functional network connectivity (FNC [8]), related to the connectivity between ICNs, and (2) power spectra of ICN time courses, related to level of coherent activity within an ICN [9].

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II. MATERIALS AND METHODS

A. Imaging Data Acquisition

Data was collected from twenty-two healthy subjects (ten males, twelve females, average age 37.73 years) on a 3.0 T MRI scanner (GE Medical Systems, Milwaukee, WI, USA) with an 8-channel receive-only RF head coil array. Written IRB-approved informed consent was obtained from every subject prior to their participation. BOLD functional data were acquired using EFGRE3D pulse sequence (TR = 2s, TE = 30 ms, field of view (FOV) = 220×220 mm^2, acquisition matrix = 64×64, flip angle = 76^o, slice thickness = 4 mm, gap = 1 mm, number of slices = 31 slices, ascending acquisition). Subjects were instructed to remain awake as they rested with their eyes closed during the collection of 12-minute resting state scan (360 volumes).

B. Imaging Data Preprocessing

Following MR image quality assessment in MRIQC software (http://mriqc.readthedocs.io), imaging data were preprocessed using SPM12b (Wellcome Department of Cognitive Neurology, UK). Preprocessing pipeline included motion and slice time correction, coregistration, and spatial normalization into the Montreal Neurological Institute (MNI) reference space. Three Gaussian kernels with different FWHM sizes of 4, 8, and 12 mm were applied. The chosen kernel sizes are commonly used in the fMRI studies [1]–[4].

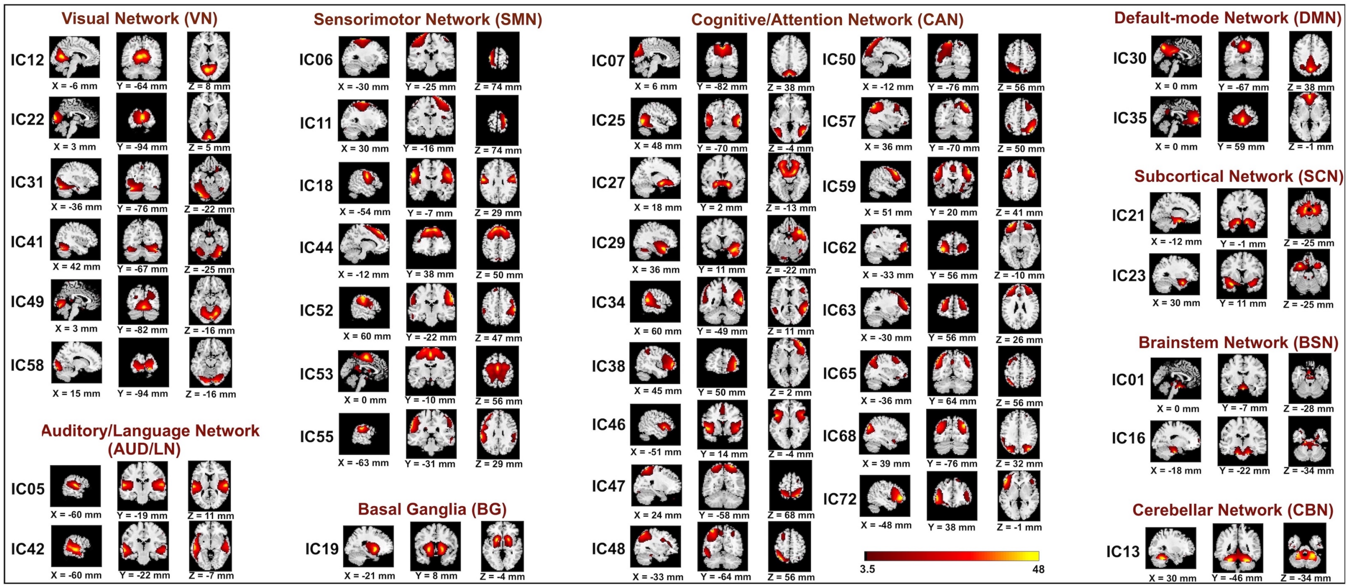

Fig. 1. Spatial maps of 40 ICNs are shown on the three most representative slices in neurological convention ($p < 0.05$, FWE corrected).

C. Group Independent Component Analysis

Group ICA with 75-IC was performed using the GIFT toolbox (GroupICAT v4.0c, University of New Mexico, USA) following a well-established ICA resting state methodology [9]. ICNs were identified based on the methodology recommended by Allen et al. [9] and our previous studies [10]–[12]. 40 components were recognized as ICNs representing valid BOLD signals and classified into one of the visual (VN), auditory/language (AUD/LN), sensorimotor (SMN), basal ganglia (BG), cognitive and attention (CAN), default mode (DMN), subcortical (SCN), Brain stem (BSN), and cerebellar (CBN) networks (Fig. 1).

D. Functional Network Connectivity and Spectral Analyses

Prior to connectivity analysis, ICN time courses were detrended, despiked, and bandpass filtered at [0.01–0.15 Hz]. Both maximal time-lagged correlation and FNC without time lag consideration were used to compute Pearson's correlation values [8] between ICNs. Fisher r-to-z transformation was applied to normalize the FNC correlation values. Power spectra were computed for each subject's time courses and separately for each smoothing condition [9]. Analyses focused on full range of the frequency bands, i.e., [0.00 - 0.25] Hz. To determine which FNC correlations or spectral bins were influenced by the spatial smoothing kernel size, paired t-test was performed at FDR-corrected $p < 0.01$.

III. Results

FNC correlations (with and without time lags) are shown for each smoothing condition in Fig. 2. Significant FNC differences at FDR-corrected $p < 0.01$ are shown in Fig. 3 for all ICNs (top), and for network average (middle) and as connectogram (bottom). Significant differences in FNC correlations with lags were also found at an exploratory, uncorrected $p < 0.01$ (Fig. 4). Results summarizing the effects of smoothing on ICN power spectra are shown in Fig. 5 (FDR-corrected $p < 0.01$).

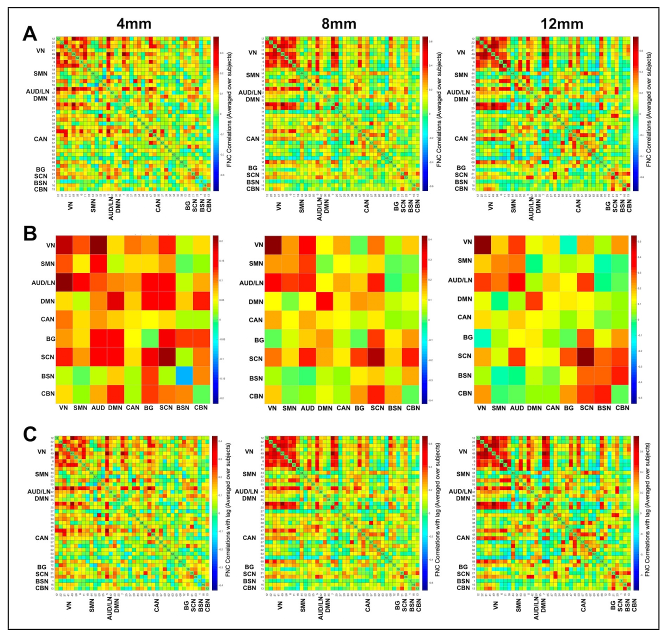

Fig. 2. **A** FNC correlations **B** FNC correlations network domain averaged **C** FNC correlations with lags. FNC values were averaged over all subjects ($n = 22$), and shown for three conditions with different spatial smoothing kernel sizes: **A** 4 mm, **B** 8 mm, and **C** 12 mm FWHM.

IV. Discussion & Conclusions

Spatial smoothing is generally a stable part of pre-processing pipeline implemented through the use of a Gaussian kernel with a certain FWHM. Using a relatively high-level ICA as a data driven methods to decompose BOLD resting state data to fine-grained ICNs, we observed that compared to data that were preprocessed using larger FWHM spatial smoothing kernel sizes, smaller kernels influenced the between-network connectivity strength by generally decreasing the FNC correlations. This effect was shared among most ICNs in particular, the VN, SMN, AUD/LN, SCN and a variety of CANs including the dorsal and ventral attention networks, central executive, and

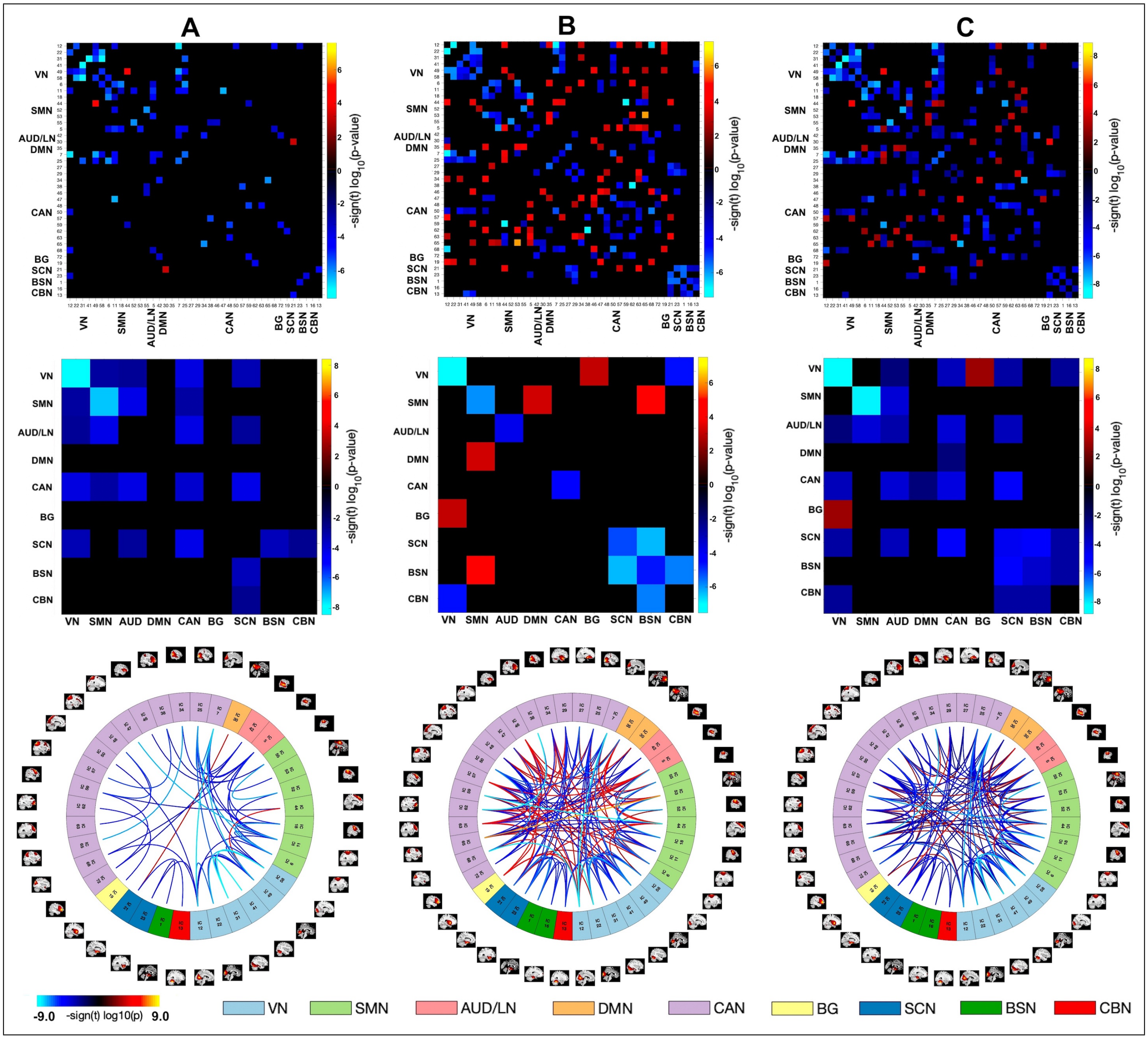

Fig. 3. Significant differences in FNC correlations for **A** S4 – S8, **B** S8 – S12, and **C** S4 – S12, where S is smoothing kernel sizes of 4, 8, or 12 mm. For each paired t-test, results are shown for all ICNs (top row), domain averaged (middle row) and as connectogram (bottom row). FDR corrected-$p < 0.01$.

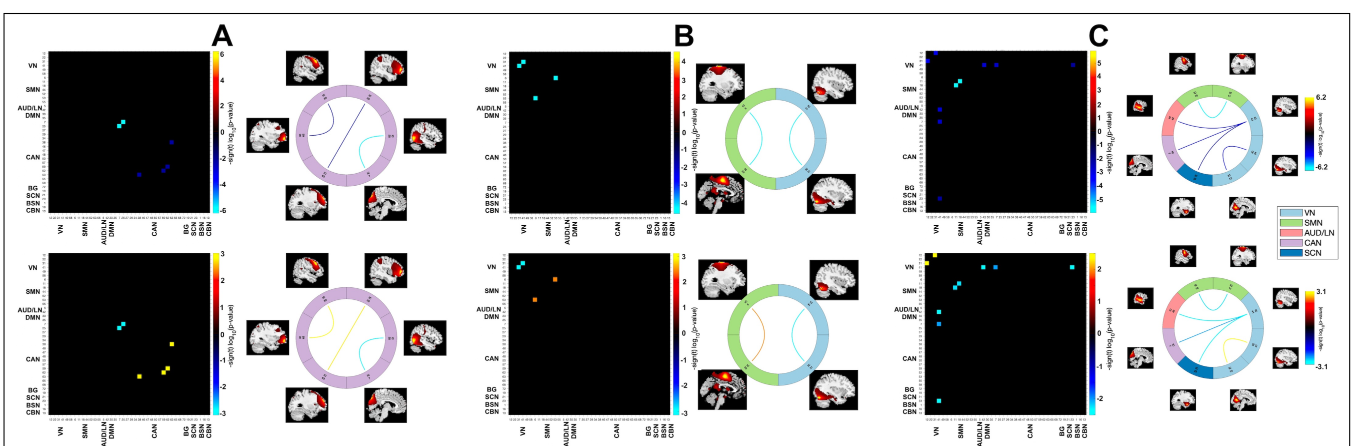

Fig. 4. Significant differences in FNC using lags are shown for **A** S4 – S8, **B** S8 – S12, and **C** S4 – S12. For each paired t-test, significant effects of FNC with lags (top) and significant effects of lags in seconds (bottom) are visualized as heatmap (left) and as connectogram (right). Uncorrected-$p < 0.01$.

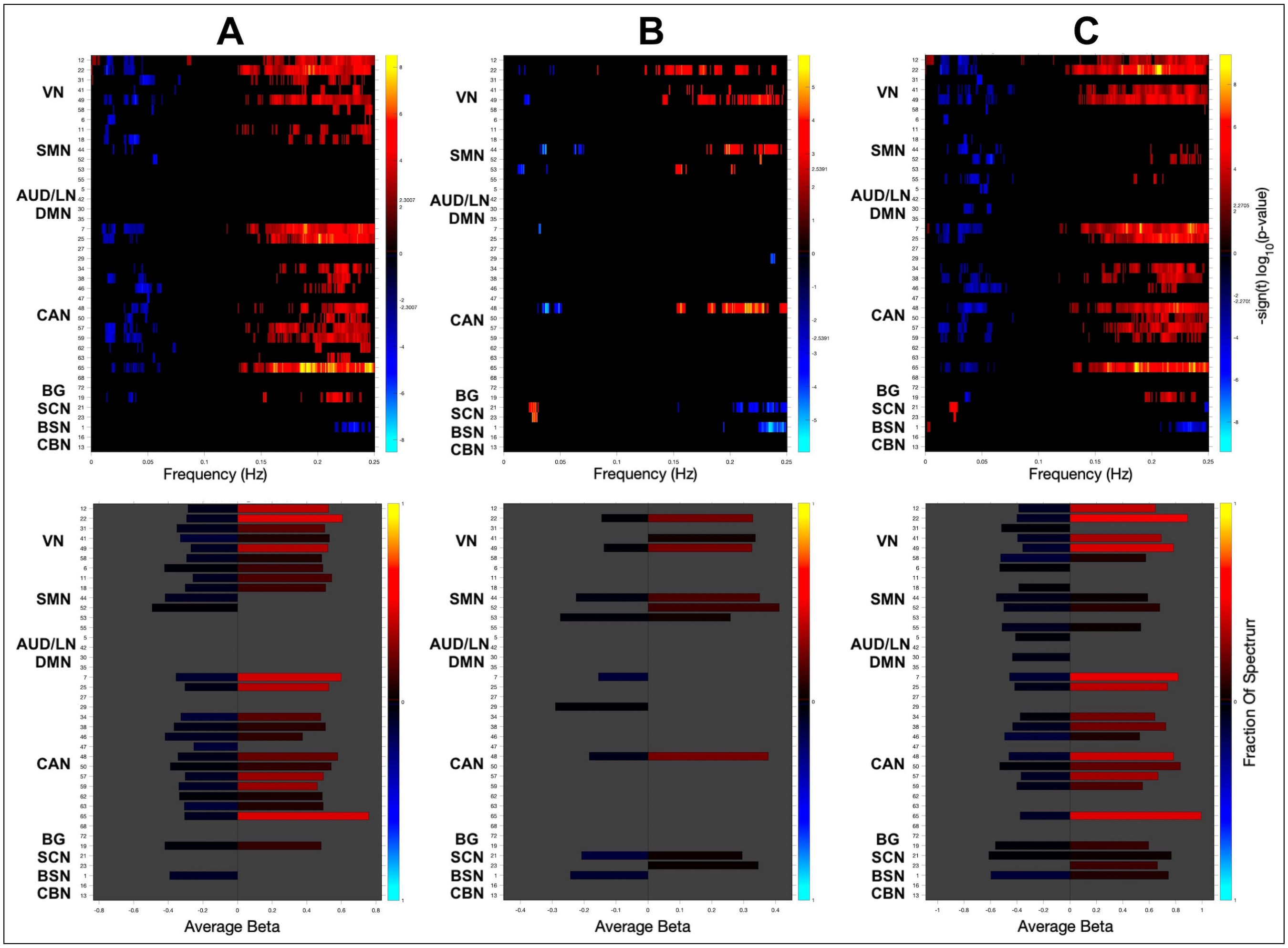

Fig. 5. Significant effects of smoothing kernel sizes on power spectra. **A** S4 – S8, **B** S8 – S12, and **C** S4 – S12, where S is smoothing kernel sizes of 4, 8, or 12 mm. *T*-maps of the significant effects are shown as composite *t*-maps. Beta-values are averaged over significant clusters. (FDR corrected-$p < 0.01$).

salience networks. There were a few exceptions. Notably, there was an increase in FNC correlations when we compared S8 condition to S12 (i.e., S8 – S12, Fig. 3B) involving DMN, BG, and BSN. The analysis of BOLD power spectra further revealed an increased high-frequency power (0.15 – 0.25 Hz) but a decreased low-frequency power (0.01 – 0.10 Hz) with a decrease in the smoothing kernel size. These findings provide a preliminary observation on how smoothing kernel size influences resting state FNC and BOLD power spectra. To further elucidate the effects of preprocessing step such as spatial smoothing on ICA network features, future studies using larger sample sizes are needed.

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