

DELAY DISCOUNTING IS PREDICTED BY SCALE-FREE DYNAMICS OF DEFAULT MODE NETWORK AND SALIENCE NETWORK

ZHIYI CHEN,^{a†} YIQUN GUO^{a†} AND TINGYONG FENG^{a,b,*}

^a Faculty of Psychology, Southwest University, Chongqing, China

^b Key Laboratory of Cognition and Personality, Ministry of Education, China

Abstract—Resting-state functional Magnetic Resonance Imaging (rs-fMRI) is frequently used as a powerful technology to detect individual differences in many cognitive functions. Recently, some studies have explored the association between scale-free dynamic properties of resting-state brain activation and individual personality traits. However, little is known about whether the scale-free dynamics of resting-state function networks is associated with delay discounting. To address this question, we calculated the Hurst exponent which quantifies long-term memory of the time series in resting-state networks (RSNs) identified via independent component analysis (ICA) and examined what relationship between delay discounting and the Hurst exponent of RSNs is. ICA results showed that entire nine RSNs were successfully recognized and extracted from independent components. After controlling some covariates, including gender, age, education, personality and trait anxiety, partial correlation analysis revealed that the Hurst exponent in default mode network (DMN) and salience network (SN) was positively correlated with the delay discounting rates. No significant correlation between delay discounting and mean Hurst exponent of the whole brain was found. Thus, our results suggest the individual delay discounting is associated with the dynamics of inner-network interactions in the DMN and SN, and highlight the crucial role of scale-free dynamic properties of function networks on intertemporal choice. © 2017 Published by Elsevier Ltd on behalf of IBRO.

Key words: delay discounting, long memory, resting-state networks, independent component analysis.

*Correspondence to: T. Feng, School of Psychology, Southwest University, No. 2, Tian Sheng RD., Beibei, ChongQing 400715, China. Fax: +86-23-68253629.

E-mail address: fengty0@swu.edu.cn (T. Feng).

[†] Zhiyi Chen and Yiqun Guo contributed equally to this work.
Abbreviations: ASD, autism spectrum disorders; AUC, area under the curve; CEN, central executive network; CSF, cerebrospinal fluid; DMN, default mode network; EPI, echo-planar imaging; ESVN, extra-striate visual network; FoV, field of view; ICA, Independence Component Analysis; LPFN, left-lateralized frontoparietal network; NEO-PI, NEO Personality Inventory; NREM, non-rapid eye movements; PCA, principal component analysis; PVN, primary visual network; rs-fMRI, Resting-state functional Magnetic Resonance Imaging; RSNs, resting-state networks; SMN, sensorimotor network; SN, salience network; TAI, Trait Anxiety Inventory; TE, echo time; TR, repetition time; VBM, voxel-based morphometry; WM, white matter.

<http://dx.doi.org/10.1016/j.neuroscience.2017.08.028>

0306-4522/© 2017 Published by Elsevier Ltd on behalf of IBRO.

INTRODUCTION

Intertemporal choice involves tradeoffs among costs and benefits occurring at different time points, which is always vital and ubiquitous in many aspects of our life, including health, education, marriage, financial investment, environmental protection and public policy. In such intertemporal choices, individuals generally prefer to smaller but immediate gratifications rather than larger but delayed one, which refers to delay discounting (Bickel et al., 2009; Hariri et al., 2006). Steep delay discounting generally related to sensation seeking (Reynolds, 2006), obesity (Weller et al., 2008), overeating (Appelhans et al., 2011) and addictive behaviors, such as pathological gambling (Dixon et al., 2003), illicit drug abuse (Heil et al., 2006; Bickel et al., 2007) and cigarette smoking (Reynolds et al., 2004; Reynolds, 2006). To date, previous studies have explored delay discounting using multi-model neuroimaging methods, such as task-state fMRI, resting-state functional connectivity and voxel-based morphometry (VBM). However, few studies indirectly explored the relationship between the scale-free dynamic properties of resting-state function networks and delay discounting.

Individual preference for delayed rewards is often quantified with discounting rates that are relatively stable over a long period of time (Kirby, 2009). To date, various neuroimaging methods have been conducted to understand the neural mechanism underlying delay discounting. Task-state functional magnetic resonance imaging (fMRI) studies have suggested that delay discounting recruits three different function networks: reward valuation network (e.g. ventromedial prefrontal cortex posterior cingulate cortex and, ventral striatum), cognitive control network (e.g. dorsolateral prefrontal cortex, anterior cingulate cortex) as well as prospection network (e.g. amygdala and hippocampus) (Kable and Glimcher, 2007, 2011; McClure et al., 2004; Peters and Büchel, 2010). In addition, structural MRI studies also revealed that two neuroanatomical networks are implicated in such economic decision, namely money network (e.g. right prefrontal cortex and parietal cortex) and time network (e.g. right parahippocampus, right hippocampus) (Yu, 2012). The resting-state fMRI studies further showed that the resting-state functional connectivity between brain regions involved in temporal discounting (such as posterior cingulate cortex, anterior insular cortex) significantly correlates with individuals' discounting rates (Schmaal et al., 2012; Li et al., 2013). Overall, these findings suggest that the neural correlates of delay discounting have

a close relationship in a portion of neural networks. However, few studies indirectly investigate whether the scale-free dynamic properties of the resting state networks (RSNs) are associated with delay discounting.

In general, resting-state functional networks always exhibit scale-free dynamic properties in corresponding time series, which are measured using the Hurst exponent (Ciuciu et al., 2013; He, 2011). Hurst exponent directly reflects fractal dimension of resting-state BOLD signals and is utilized for the measures of “long-term memory”, showing the regularity (or self-similarity) of spontaneous brain activity across voxels or networks (Maxim et al., 2005). High Hurst exponent indicates persistently coherent processes (or activity) of time series (long-term memory effect) at resting state, which makes the following signals from last phase become predictable (Park et al., 2010). When Hurst exponent range from 0.5 to 1, it implies the positive-phase sustained time series. However, closing or less equal to 0.5 indicates biased fractional brownian motion for the time series, namely random noises. Prior literatures revealed that the alteration of Hurst exponent in RSNs or hub regions of RSNs is highly associated with psychiatry and psychological conditions, including major depressive disorder, autism spectrum disorders (ASD), social anxiety, non-rapid eye movements (NREM) sleep and personality trait (Wei et al., 2015; Lai et al., 2010; Gentili et al., 2017, 2015; Lei et al., 2013; Xu et al., 2015). Collectively, sufficient evidence suggests delay discounting is associated with temporal scaling properties of RSNs (Ortner et al., 2013), but this association has not been studied to date. Hence, it is necessary to investigate the impact of the scale-free dynamic properties of intrinsic RSNs on delay discounting, as it might provide a further understanding of intertemporal choice.

In the present study, we explored what association between delay discounting and the scale-free dynamic properties of RSNs is. Prior literatures have shown that independent component analysis (ICA) is one of the most powerful methods to recognize intrinsic brain network from BOLD signals and identify certain low-frequency patterns (Bordier et al., 2010; Klados et al., 2011; Kopřivová et al., 2013; Kiviniemi et al., 2003). Thus, we performed ICA to extract all the independent components and accurately select all the defined RSNs. Then, we estimated the Hurst exponents that were further

utilized as classification features for clarifying scale-free dynamics of intrinsic resting-state function networks. Finally, the partial correlation analysis was conducted to examine the association between delay discounting and scale-free dynamic properties of RSNs.

EXPERIMENTAL PROCEDURE

Participants

One hundred and thirteen healthy participants were recruited in the current study, the age range from 17 to 25 years ($M = 20.461$; 35 males, 97 female), and they were paid for their participation. All participants had no history of psychiatric or neurological illness as confirmed by psychiatric clinical assessment. The experimental protocol was approved by the Institutional Review Board (IRB) of the Southwest University. Eight participants were not included in the imaging analyses due to head motion (exclude two participants), distortion on the processed fMRI (exclude two participants) and error task reacting (exclude four participants), and 105 subjects remained. The detailed demographic characteristics of them have been summarized in Table 1. No significant differences in all behavioral measures between genders were found. All participants were instructed to complete a series of behavioral measures and further finish the 8-min resting-state fMRI scan.

Measures of participants' specificity

In order to avoid the distortion or confusion of our findings due to emotional reactivity (Gentili et al., 2015) and personality trait (Lei et al., 2013; Gentili et al., 2017; Manning et al., 2014), we have measured participants' personality and mood by NEO Personality Inventory (NEO-PI) and Trait Anxiety Inventory (TAI) respectively. NEO-PI includes five sub-scales (Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness), all showing the high reliability (Costa and McCrae, 1992). TAI is designed for the assessment of individual relatively stable anxiety proneness (Spielberger, 1970). These scores of psychological evaluation would be utilized as control variables for subsequent partial correlation analyses to control potential effort of these factors.

Table 1. Participant Demographic information for the current study

Variables (mean \pm S.D.)	Male	Female	<i>t</i>	<i>p</i> -value
Number of subject	32	73		
Age (years)	20.40 \pm 2.04	20.48 \pm 2.05	−0.206	0.837
Education (years)	13.86 \pm 0.86	13.83 \pm 0.76	0.209	0.835
Big-five personality				
Conscientiousness	42.20 \pm 6.41	41.51 \pm 6.31	0.545	0.968
Extraversion	40.17 \pm 5.76	39.38 \pm 6.95	0.622	0.812
Neuroticism	34.53 \pm 8.04	34.18 \pm 6.98	0.238	0.433
Agreeableness	40.31 \pm 4.75	40.35 \pm 5.14	−0.040	0.968
Openness	41.62 \pm 5.89	40.71 \pm 5.77	0.788	0.587
Trait anxiety	53.00 \pm 10.47	53.35 \pm 9.09	−0.183	0.855

Download English Version:

<https://daneshyari.com/en/article/5737351>

Download Persian Version:

<https://daneshyari.com/article/5737351>

[Daneshyari.com](https://daneshyari.com)