Heat kernel-based network measures detect change in functional connectivity following fluid intelligence enhancing intervention

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Background: Recent advancements in neuroimaging represent brain connectivity as dynamic processes to gain deeper understanding of information transport. For this IEEE Brain Data Bank Challenge, we employ heat kernels [Chung et al. 2016] to model the process of energy diffusion in functional networks to characterise changes in functional performance with training.

Objective: **To determine if measures of information transport from brain connectivity can identify changes in brain function following intervention to improve fluid intelligence.**

Methods: Resting-state fMRI data were acquired from 25 subjects before and after 48 training sessions of an adaptive visuo-spatial and change detection task, and subsequently processed to extract correlation connectivity matrices. In this work we assess the functional connectivity of both negative (inhibitory) and positive (excitatory) connections in the brain separately, by utilising heat kernel derived measures on the graphs. Heat kernels can be used to model information flow in a network and exploited to characterise the network's efficiency for information transport. In this study we focus on the peak heat kernel value (maximum information transport) and the corresponding time at which this occurs. In order to assess the benefit of utilising a graph-theoretical approach in the data, we investigate the differences of our measures before and after training and relate it to differences in performance of the figure series task. After extracting our measures, we perform an automated anomaly detection to remove outliers using an isolation forest approach. The remaining data was used to investigate correlation and significance between change in figure series task performance versus change in heat kernel features.

Results: Paired t-test analysis on the pre- and post-training figure series performance was found to be not significant ($p = 0.155$). After calculating heat kernel measures for the networks defined by positive-correlation edge weights, we identified statistically significant differences in these measures between pre- and post-training time points as shown in Figure 1a ($p < 0.001$ for both peak value and time). Similar testing on heat kernel measures computed from networks with negative-correlation edge weights were not statistically significant. Based on the results of the isolation forest for anomaly detection, we subsequently excluded subjects 7, 12, 15 and 22, as they were considered anomalies in a consensus vote using both heat kernel measures. Correlation analyses on difference in figure series performance versus heat kernel measures

were found to be statistically significant for peak value (corr = 0.5; $p < 0.020$; Figure 1b) but not for time to peak (corr = -0.3; $p < 0.184$). Furthermore, from the colour-coded circles in Figure 2b, the greater a subject's peak value pre-training, the greater it increased post-training.

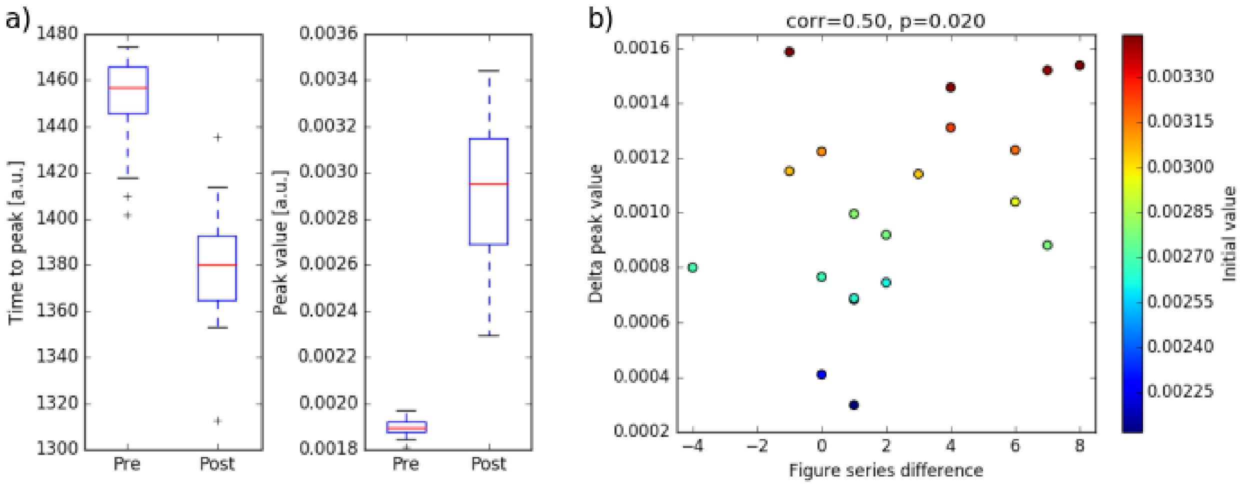

Figure 1a) Heat kernel features computed from positive correlation matrices of functional connectomes before and after cognitive training, b) Change (pre- and post-training) in peak value versus change in Figure Series scores. Each circle is a subject, colour coded according to the original peak value prior to training.

Interpretation: These findings suggest our heat kernel features to be highly sensitive to changes in brain function following interventional training. Heat kernel peak value is associated with a network's ability to transport information efficiently - where the greater the value, the greater the network's propensity for efficient information transport [Chung et al 2016]. We found subjects with a higher starting value of peak information transfer to show greater increase in this value following training. This may reflect an increase in efficiency of information transfer in the excitatory network of the brain, which is further supported through the negative correlation (although not statistically significant) of the time to peak value. This suggests potential for the heat kernel to capture information that may be predictive of subjects that are more likely to improve and benefit from fluid intelligence training.

Chung, A. W., M. D. Schirmer, M. L. Krishnan, G. Ball, P. Aljabar, A. D. Edwards, and G. Montana. 2016. 'Characterising Brain Network Topologies: A Dynamic Analysis Approach Using Heat Kernels'. *NeuroImage* 141:490–501.