## Temporally-independent functional modes of spontaneous brain activity

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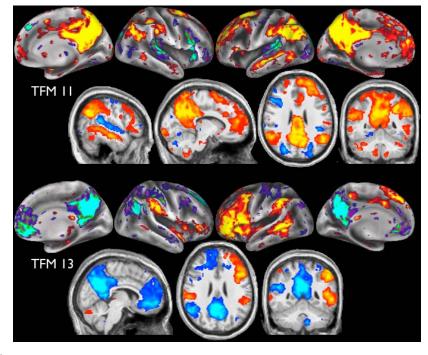
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INTRODUCTION Resting-state FMRI has become a powerful tool for studying functional networks in the brain. Even "at rest", the brain's different functional networks spontaneously fluctuate in their activity level; each network's spatial extent can therefore be mapped by finding temporal correlations between the different regions that comprise the network. Current correlation-based approaches measure the average functional connectivity between regions over time, but this average is not very meaningful for regions that are part of multiple networks; one ideally wants a network model that explicitly allows overlap, for example, allowing a region's activity level to reflect one network's activity at some points in time and another network's activity at others. However, even those approaches that do allow overlap have often maximised mutual spatial independence, which may be suboptimal if distinct networks have significant overlap. In this work we identify functionally distinct networks by virtue of their temporal independence, taking advantage of the additional temporal richness available via improvements in FMRI sampling rate. We identify several "temporal functional modes" (TFMs), for example, breaking down the default-mode network (and the regions anti-correlated with it) into several functionally distinct networks, each containing its own set of distinct correlations and anti-correlations. These functionally-distinct modes of spontaneous brain activity are, in general, quite different from resting-state networks previously reported. They account for some of the apparent nonstationarity (temporal changes in functional network structure) reported by temporal correlation analysis, and may have greater biological interpretability than some of the resting-state network patterns seen to date.

DATA & METHODS 36 x 10-minute resting-FMRI datasets from 5 healthy adults with informed consent. 3T Siemens Trio, 40mT/m, 32-channel head coil. FMRI was acquired using multiband (MB) accelerated [3,4,5] echo planar imaging with controlled aliasing [6,7]. 3 slices were simultaneously excited (MB=3), giving a whole brain temporal resolution of 0.8s (3x3x3mm). Data was analysed/visualised using FSL, FreeSurfer, FastICA and Caret. MELODIC (FSL) spatial-ICA was used to remove the majority of the artefacts from each session. We then mapped each 4D dataset into a standard representation of grey matter ("grayordinates") currently being developed for the NIH Human Connectome Project; this is a combination of cortical midgrey surface vertices and 3D sub-cortical/cerebellar voxels (from a 3D nonlinear registration of the structural to the MNI152 standard template image) [8]. We concatenated temporally all subjects' datasets, to feed into a 200-dimensional group-wise spatial-ICA and removed 58 of these components (being artefacts), leaving 142 functional "nodes" - node timeseries and associated spatial maps. The 142 timeseries were then fed into temporal-ICA (the TFM analysis) with an ICA dimensionality of 21, in order to find the 21 strongest TFMs present in the group data as a whole.

RESULTS The set of 21 TFMs was found to be robust and reproducible via split-half analyses, and several of the TFMs were also found (albeit with much less robustness) from a "standard-TR" dataset of 36 subjects' resting-FMRI data [2]. Two example TFMs are shown here, both having strong overlap with the default-mode network (DMN), but being different from one another in important respects. TFM 11 (the "semantic with default-mode" system) contains large portions of the DMN, including PCC/precuneus, anterior cinqulate and widespread angular gyrus, along with Brodmann 22 and frontal areas 9/46. These regions are very similar to the "semantic network" found in a meta-analysis of 120 semantic system studies [1]. Anti-correlated regions are less prominent, including early auditory (Brodmann 42) and higher-level visual regions. TFM 13 (the "language versus default-mode" system) also includes large and asymmetric frontal areas (more lateral than in TFM 11), and is the only TFM to strongly cover Broca's area (Brodmann 44). This forms part of a strongly lateralised "language" network, including bilateral supramarginal gyrus, which anti-correlates with much of the known DMN (without including auditory), with the medial-frontal part of the DMN being strongly lateralised towards the right.

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