Information Transfer in the Brain Is Synergistic

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Abstract

Complex behaviour relies on the coordination of distributed neural processes, enabled by information transfer between brain regions. Despite progress in time-resolved and directed connectivity analysis, how information actually flows in the brain remains unclear. Here, we use a novel decomposition of information transfer based on Partial Information Decomposition (PID) to analyse spontaneous BOLD fMRI dynamics. We find that transfer is dominated by temporally and informationally integrated, synergistic interactions. These findings offer a fine-grained and interpretable approach to brain dynamics, opening new potential links to cognition.

Keywords: information transfer; information flow; synergy; brain dynamics; partial information decomposition

Introduction

Information transfer in neuroimaging data is usually estimated using information-theoretic measures such as Granger Causality or Transfer Entropy (Barnett, Barrett, & Seth, 2009; Schreiber, 2000; Bossomaier, Barnett, Harré, & Lizier, 2018). Briefly, these measures estimate the degree to which predicting the future of a target brain region Y is improved by knowing the present of a source region X, given the target's present—i.e., $I(Y_{t+1};X_t|Y_t)$. This approach has been successfully applied across neuroscience, for instance to identify integrative regions of the 'global workspace' by their ratio of all incoming and all outgoing information (Deco, Vidaurre, & Kringelbach, 2021).

However, the total information transfer can be further decomposed into two modes: one that depends on the state of the target region and one that is independent, directly influencing the future of the target region (Williams & Beer, 2011). Only the state-independent component aligns with the usual interpretation of transfer entropy as a transfer or flow of information, while the state-dependent mode implies a more interactive process that can only be read out by knowing the past of both variables, but from neither of them separately (*Fig. 1*).

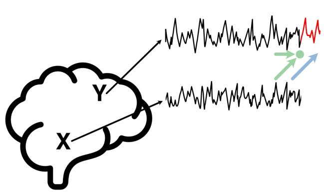

Figure 1: **Illustration of information transfer between two brain regions.** Synergy depends on the state of the target region (green), while unique does not (blue).

This decomposition can be formalised using Partial Information Decomposition (PID) (Williams & Beer, 2010), where state-dependent transfer is measured by synergy, and state-independent transfer is the unique information from source X to target Y (*Fig. 2*). The full PID of the total mutual information $I(Y_{t+1};Y,X)$ also includes a redundant component (overlapping information between X_t and Y_t) and the unique information from Y to Y_{t+1}, corresponding to storage in Y.

Here, using the PID decomposition on resting-state fMRI data, we show that information transfer in spontaneous brain dynamics is fully captured by synergy, with no unique information present. Furthermore, we develop a method to unwrap the global synergy into sample-by-sample time-resolved sequences of synergy. These show that synergy has intermittent dynamics with relatively few peaks in many brain regions simultaneously driving the global average.

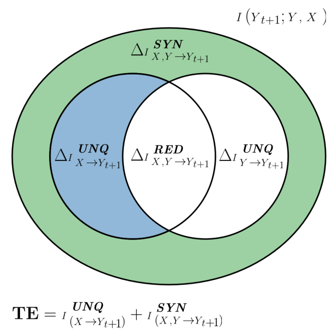

Figure 2: **Partial Information Decomposition.**

Methods

Data

We use the publicly available data from the Human Connectome Project (Van Essen et al., 2013). We choose a sample of 1003 participants from the 2017 release of the data. We obtain ~ 15 minutes of resting-state data and preprocess them according to the same steps as in Deco, Sanz Perl, et al. (2021). We use the Desikan-Killiany parcellation with 62 cortical and 18 subcortical regions.

Analysis

For all pairs of brain regions X and Y, we use PID to decompose the total mutual information $I(Y_{t+1};Y,X)$ into four PID information atoms: $\Delta I^{RED}_{X,Y\to Y_{t+1}}$, $\Delta I^{UNQ}_{X\to Y_{t+1}}$, $\Delta I^{UNQ}_{Y\to Y_{t+1}}$ and $\Delta I^{SYN}_{X,Y\to Y_{t+1}}$. The transfer entropy $I(Y_{t+1};X_t|Y_t)$ is the sum of $\Delta I^{UNQ}_{X\to Y_{t+1}}$ and $\Delta I^{SYN}_{X,Y\to Y_{t+1}}$ (*Fig. 2*).

We calculate all quantities using five-timestep Taken's embeddings of source variables (i.e., the equations use a simplified notation when they show only time t). We then normalise all results by the total mutual information to find the relative contribution of each atom (Deco, Sanz Perl, et al., 2021; Martínez-Sánchez, Arranz, & Lozano-Durán, 2024).

There is no canonical measure to obtain the PID decomposition. Here, we use the measure $Idep$ that is based on dependency constraints between the variables (James, Ayala, Zakirov, & Crutchfield, 2018; Kay & Ince, 2018). The key advantage of this measure is that it primarily estimates the unique values (as opposed to redundant atom as most other

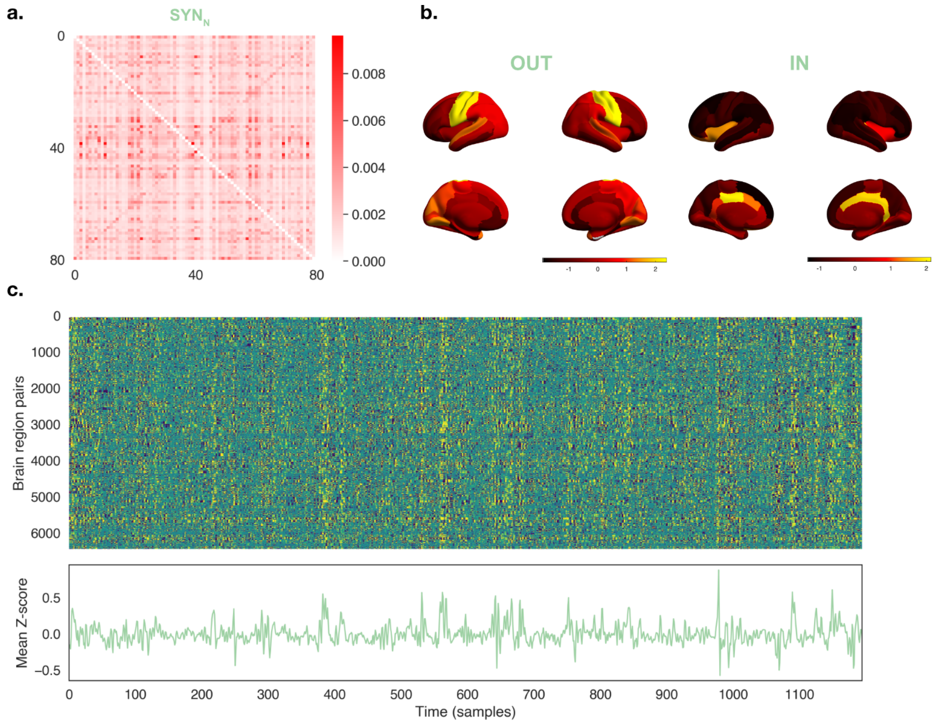

Figure 3: **Synergy in spontaneous brain dynamics.** **a,** Mean synergy normalised by total mutual information for 1003 participants across all pairs of 80 brain regions. **b,** Sum of all incoming (rows) and outgoing (columns) information, z-scored and shown on a brain surface. **c,** Local synergy for an illustrative participant. Z-scored and shown from -1 to 1 (above) and as a mean across all pairs of brain regions (below).

measures), making it suitable for an analysis that focuses on this atom.

To calculate local PID, we unravel $Idep$ using pointwise entropies instead of global entropy. Note that this approach is not a general solution for local PID, as the mean of the local values is not guaranteed to converge to the global value. However, in the case of our data, the difference is no larger than 0.0001.

Results

We find that information transfer is dominated by synergy, capturing > 0.99 of the variance in transfer entropy (*Fig. 3*a). Summing all incoming information to each brain region and all outgoing information from each brain region we find, similar to Deco, Vidaurre, and Kringelbach (2021), that while some sensory-motor regions are dominated by outgoing synergy, incoming synergy dominates in higher-order integrative brain regions (*Fig. 3*b).

We then calculate local PID (shown here for one illustrative participant). We find that synergy follows an intermittent dynamic, with transient moments of high synergy across most of the brain driving the globally observed synergy. Our approach is inspired by Zamani Esfahlani et al. (2020), where the authors employ a local measure of correlation to find similar dynamics. However, we find synergy to be unrelated to their measure ($cos(\Theta) = 0.054$ for this participant). We do, however, find that the redundant atom is related to the measure employed by Zamani Esfahlani et al. (2020) ($cos(\Theta) = 0.720$).

Discussion

Using fine-grained analysis of the interactions between brain regions in fMRI data, we demonstrate that synergy dominates neural interactions, highlighting the limitations of traditional transfer measures. Moreover, we show that synergy follows intermittent dynamics, which are orthogonal to the dynamics of correlation.

Overall, these results suggest that information transfer in the brain is informationally and temporally integrated. More broadly, our methods—being temporally resolved and interpretable—pave the way for more meaningful links between brain dynamics and cognition.

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