Spatiotemporal information transfer pattern differences in motor selection

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1. Introduction

Issue: Analysis of information transfer in brain images (e.g. [1]) typically focuses on **average** information transfer (i.e. transfer entropy [3]). Yet the dynamics of transfer from a source to a destination can also be quantified *at individual time points* using the local transfer entropy (TE) [2], and this local perspective is known to reveal dynamical structure that the average cannot.

We present a method to quantify **local** TE values in time between source and destination regions of variables in brain-imaging data, combining:

- computation of *inter-regional* transfer between two regions of variables (e.g. voxels) [1], with
- the *local* perspective of the dynamics of such transfer in time [2].

We apply the method to a motor-selection experiment, showing significant differences in the local information transfer into left and right motor cortices *at specific time points*, depending on which motor-selection was made. Thus, **the technique shows promise** for revealing local information transfer dynamics in other cortical data sets.

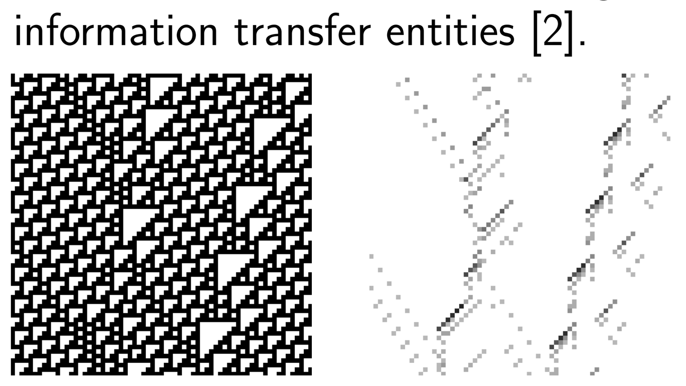
2. Local interregional transfer

Local transfer entropy [2, 3] $t(Y \rightarrow X, n)$ is the amount of information transferred from a source to a destination at a specific time point n:

$$t(Y \rightarrow X, n) = \log_2 \frac{p(x_{n+1} | x_n^{(k)}, y_n)}{p(x_{n+1} | x_n^{(k)})} \quad (5)$$

$$T(Y \rightarrow X) = \langle t(Y \rightarrow X, n) \rangle_n \quad (6)$$

It is useful for studying the dynamics of information in a system, rather than simply describing the average relationship between a source and destination. E.g. in Cellular Automata, the local TE shows that gliders are the dominant information transfer entities [2].

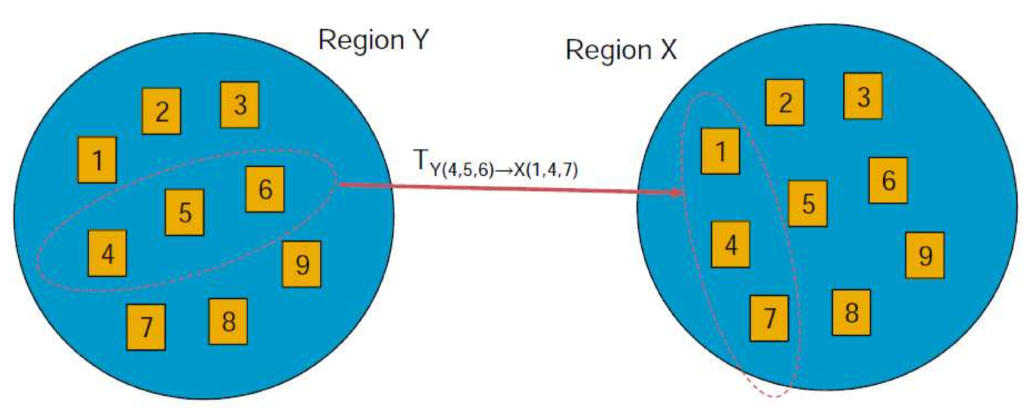


CA rule 110 (raw states and local transfer).

Now, **Multivariate TE** $T(\mathbf{Y} \rightarrow \mathbf{X})$ is an extension of TE to multivariate source $\mathbf{Y}$ and destination variables $\mathbf{X}$ → this captures interaction-based transfer (e.g. in XOR operations). For fMRI, it's tempting to measure multivariate TE between all voxels in two regions, but this is impractical.

So, define: **Interregional TE** $T_v(\mathbf{R_a} \rightarrow \mathbf{R_b})$ from region $\mathbf{R_a}$ to $\mathbf{R_b}$ as the expectation value of multivariate TEs over a large number S of subsets $\mathbf{R_{a,i}}$ and $\mathbf{R_{b,j}}$ of v variables from each region [1]:

$$T_v(\mathbf{R_a} \rightarrow \mathbf{R_b}) = \langle T_v(\mathbf{R_{a,i}} \rightarrow \mathbf{R_{b,j}}) \rangle_{i,j} \quad (7)$$



Local Interregional TE is then the average *local* transfer between multivariate sets $\mathbf{R_{a,i}}$ of v variables in region $\mathbf{R_a}$ to variables $\mathbf{R_{b,j}}$ in region $\mathbf{R_b}$ at time n:

$$t_v(\mathbf{r_a} \rightarrow \mathbf{r_b}, n) = \langle t_v(\mathbf{R_{a,i}} \rightarrow \mathbf{R_{b,j}}, n) \rangle_{i,j} \quad (8)$$

Importantly: (8) provides precise values for precise time points (no sliding windows), and there is no voxel selection involved.

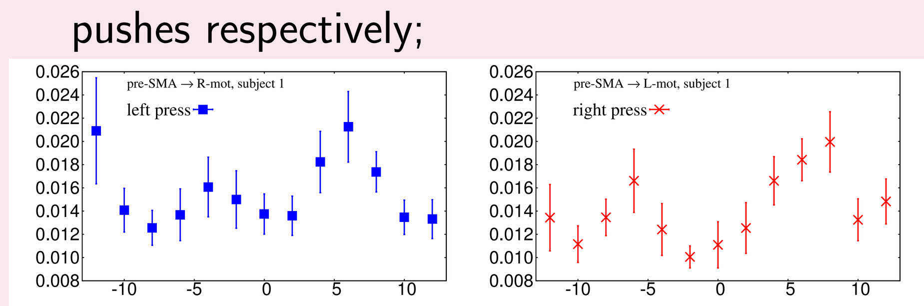
3. Differences in local transfer

Algorithm 1 to analyse whether the local transfer from region $\mathbf{R_a}$ to $\mathbf{R_b}$ *differs* between two event types L and R at the same time points n_r *relative* to the events:

Subject level

1. **Compute TEs** for S subsets from region 1 and 2 as per (7);
2. **Compute mean of local TEs** for all subsets S at each time n as per (8);
3. **Redistribute** these local TEs into populations:
   - **for each time point** $n_r = -T \dots -2, 0, 2 \dots T$ **relative** to the event times, and
   - separately **for each event type**.

   We have e.g. population means $\overline{t_v(\mathbf{r_a} \rightarrow \mathbf{r_b}, n_r)_L}$ and $\overline{t_v(\mathbf{r_a} \rightarrow \mathbf{r_b}, n_r)_R}$ at each relative time n_r for left and right button pushes respectively;

4. **z-test** for significant differences between the population means for each event type (here $\overline{t_v(\mathbf{r_a} \rightarrow \mathbf{r_b}, n_r)_L}$ and $\overline{t_v(\mathbf{r_a} \rightarrow \mathbf{r_b}, n_r)_R}$) at each time point n_r relative to the events (using $p < \alpha$ and correcting for multiple comparisons due to multiple regions and relative time points).

Group level

1. **Binomial test**: is there a significant number of subjects with a significant difference between local TEs for the different events, at each relative time step (correcting for multiple comparisons again)?

Prediction of event type

1. Use 70% of the events to determine threshold levels for local TEs for each event type.
2. Use 30% of the events to test whether these thresholds are useful for predicting the event type (z-test of success rates across subjects compared to null hypothesis of 50%).

4. Motor selection experiment

Data from (Libet-style) experiment first reported in [4]:

- fMRI recorded from 7 localized regions (left- and right-motor cortex, SMA, pre-SMA, lateral and medial frontopolar cortex, precuneus) in 12 subjects;
- Subjects asked to freely decide whether to push one of two buttons (with *left* or *right* index finger), whenever they felt the urge to do so, and to press the button immediately on deciding.

The original analysis in [4] (machine learning, multivoxel, on single regions) could:

- Decode the button push with up to 75% accuracy;
- Make (statistically significant) predictions up to 8 seconds before the push occurred.

With interregional local TE we can expect to see:

- Differences in local interregional transfer between two conditions at specific event-related time steps.
- Differences in roles of different voxels within regions.

5. Results

With Algorithm 1: there were no significant local TE differences between event types at the group level.

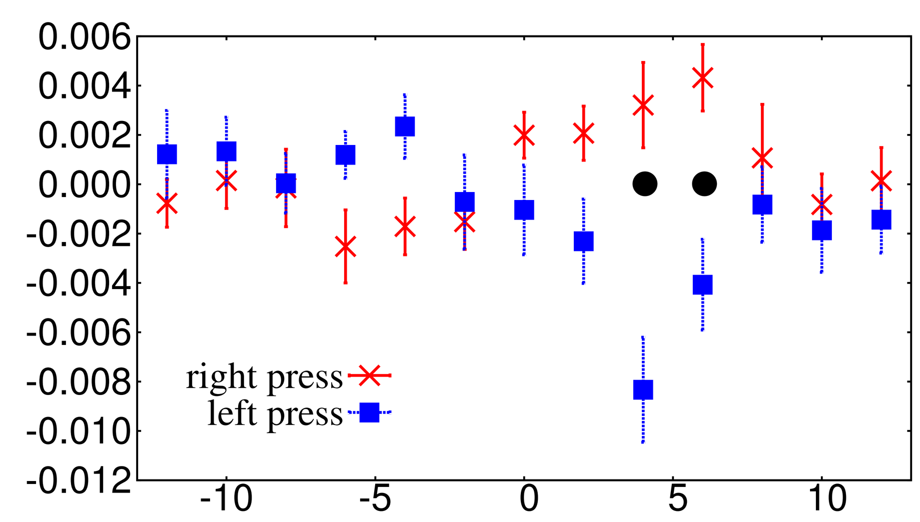
Two particular challenges to our analysis:

1. There is a lot of activity and transfer that is irrelevant to the task;
2. The timing of the user's actions is not precise.

Two enhancements address these:

1. Examine **differences** $\overline{(t_v(\mathbf{R_a} \rightarrow \text{L-mot.}, n_r)} - \overline{t_v(\mathbf{R_a} \rightarrow \text{R-mot.}, n_r))}$ to focus on task-related transfer (**Algorithm 2**);
2. And **aggregate** local TE differences over multiple consecutive time steps (**Algorithm 3**).

Sample results (Algorithm 2, $v = 2$ voxels)
Difference between transfer from pre-SMA to left and right motor cortex versus time n_r after button press for subject 1 (significant diffs. at bullets):



Summarised results
Only the pre-SMA as a source region produced significantly different transfer values into L-motor and R-motor at the group level (v = num. joint voxels):

Technique	Subjects with sig. diffs. * = sig. at group level	Predictive performance (where significant)
Algorithm 1	0	-
Algorithm 2	4* ($v = 2$)	65.5 %
Algorithm 3 (most robust)	5* ($v = 1$) 5* ($v = 2$) 5* ($v = 4$)	- 67.3 % -
Algorithm 3 using average region activity	5*	-

6. Conclusion and Outlook

Novelty: first analysis of transfer entropy on a local temporal scale in brain-imaging data (at specific time points).
Features: functions at the regional level, accounts for multivariate interactions and handles non-linearity.
There are no known similar techniques to produce local values from *linear* techniques (e.g. Granger causality).
Results: confirms *some* expected differences in transfer into left and right motor cortices based on experimental conditions. We found slight improvements with:

- Voxel-level analysis compared to average over regions.
- Multivariate (multi-voxel) analysis.

Promise for revealing transfer dynamics in other data sets.
Voxel selection: is not used here (advantage) but adding this could improve the technique.

References

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