DECODING FUNCTIONAL MRI DATA USING SPFM AND TEMPORAL ICA: A VALIDATION STUDY

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TARGET AUDIENCE: Neuroimaging researchers and neuroscientists.

INTRODUCTION: Most fMRI studies map task-driven activities in response to block/event-related paradigms. It would be extremely beneficial to be able to decode the mental activity of the brain while at rest, when spontaneous brain activity occurs without any attributed task or known timing. Sparse Paradigm Free Mapping (sPFM) is a regression technique based on linear haemodynamic convolution that can detect the timing and spatial distribution of activation events in the resting state[1], but the problem of relating these detected events to function remains. Temporal Independent Component Analysis (tICA) can be used to compress fMRI time courses, by decomposing the data into a series of temporally independent components (potentially relating to events) with associated, potentially overlapping, spatial maps. However tICA generally suffers from low signal-to-noise ratio when applied to fMRI data; this can be improved by the noise reduction provided by sPFM. The tICA spatial maps could then be decoded by comparison to meta-analyses of task driven fMRI data.

AIM: (1) To validate the use of sPFM and tICA to extract the timing of discrete motor movements. (2) To determine the feasibility of decoding the discrete spatial maps resulting from sPFM and tICA using meta-analyses.

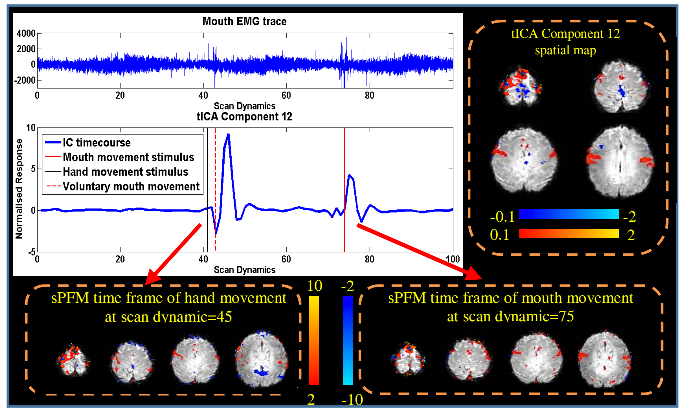

Figure 1: *Subject 2 tICA component 12 corresponding to 2 periods of activity detected in sPFM; scan dynamic 45: Task driven left hand movement with voluntary mouth movement (see EMG trace) Scan dynamic 75: Task-driven mouth movement. tICA component map shows a combination of the mouth and hand movement, classified by meta-analysis as mouth movement.*

METHODS: Five subjects were scanned on a Philips 7T Achieva system. *fMRI paradigm:* 5 minutes of a motor task involving six types of discrete movement (movements of right or left toes or hand, eye blinks, each performed 3 times in 3 s, and a single swallow in a 3 s period), each movement was performed twice in random order. A fixation cross was displayed which was replaced by a visual cue to instruct the subjects to perform each movement. A random inter-stimulus interval (mean 20 s) was left between each movement and the next instruction. Electromyography (EMG) [Brain Products, Munich, Germany] was recorded throughout the fMRI scan to detect muscle activity, bipolar electrode pairs were placed on both legs, hands, the right eye and on the neck. EMG data were corrected for gradient and pulse artefact [Brain Vision Analyzer2], and were visually inspected to detect peaks/waveform patterns reflecting movements. The fMRI data was realigned [SPM8], physiological noise corrected [RETROICOR], spatially smoothed with a 4x4x4 mm Gaussian kernel, low frequency drift corrected, and normalised to compute percentage signal change. sPFM was run on the data, to produce an activation time series (ATS) per voxel. For voxels within the sensorimotor network (PreCG, PostCG and SMA [Harvard-Oxford cortical atlas]), the ATS was convolved with a canonical HRF [SPM8], and tICA [fastICA] was applied with 20 components. Each tICA component was then compared to the EMG traces, and related to a particular task by visual inspection. The corresponding tICA spatial map was also classified into movement types by first performing a meta-analysis to generate a metamap for each task type [BrainMap[2-3]], and then multiplying the tICA spatial map weighting with each metamap Activation Likelihood Estimate weighting. The movement task that resulted in the highest resulting weighting was assigned to that tICA component.

RESULTS: Table 1 shows for each subject the number of movement-related events (task-driven (I) or voluntary (II) events) which were detected by tICA and apparent in the EMG trace, and in brackets the corresponding number of task-driven events correctly classified using the metamaps. Some tICA components identified events that could not be attributed to any task-driven or EMG-detected voluntary movement, or noise pattern (III). Subject 3 showed excessive head movement. Excluding Subject 3, the average success rate for detecting task-driven events (without using any prior knowledge of timing or nature of events) across subjects was 94 %, of these 78 % were also classified to the correct task using the meta-analysis. Figure 1 shows tICA component 12 for Subject 2, the time course of which shows two events. These are reflected in the corresponding sPFM activation maps as task-driven left hand movement rapidly followed by a voluntary mouth movement at scan dynamic 45, and a task-driven mouth movement at scan dynamic 75. The tICA component spatial map reflects these combined movements.

Subject	I Task-driven events							II	III
	Left Hand	Right Hand	Mouth	Eye	Left Foot	Right Foot	Total detected events from 12 movements	Number of voluntary movement events detected by tICA / EMG	Number of ICs not associated with stimuli or EMG
1	2(2)	2(2)	2(2)	2(1)	2(2)	2(2)	12 (11)	2 / 2	4
2	2(1)	2(1)	2(2)	1(1)	2(1)	1(2)	10 (8)	2 / 2	4
3	2(2)	0(0)	1(1)	0(0)	0(0)	1(0)	5 (4)	5/ 11	13
4	2(2)	2(1)	2(2)	2(2)	2(0)	2(2)	12 (9)	2 / 4	4
5	2(0)	2(2)	2(0)	1(1)	2(2)	2(2)	11 (7)	0 / 0	9

Table 1: ***I****) Number of task driven movement-related events detected by tICA and apparent in EMG shown for all subjects; the number of these events correctly classified by meta-analysis are shown in brackets.* ***II****) Number of voluntary non-task driven movement-related events detected by tICA as a ratio of the number of additional events detected by EMG.* ***III****) Number of independent components (IC) that were not associated to any of the task-driven or non-task driven events, such as noise components.*

DISCUSSION: The use of tICA combined with sPFM to detect events with no prior knowledge of their type or timing, has been validated using a series of discrete motor tasks and EMG. Meta-analysis successfully classified 78 % of task-driven events identified by tICA and detected in EMG. In addition, some tICA components detected events which were not attributable to noise, task or EMG-detected voluntary movements. These require further investigation but may involve movements not detected by EMG.

CONCLUSION: This method will now be applied to decode spontaneous events in resting state data, and the mapping of events extended to whole brain functional areas using meta-analyses of other cortical networks. **REFERENCES:** 1. Caballero Gaudes et al, HBM. 2011;34(3): 501-18. 2. Eickhoff HBM 2009; 30, 2907-2926. 3. Laird et al Neuroinformatics 2005; 3, 65-78. **Acknowledgements**: This work was funded by the Medical Research Council.

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