

**Decoding fMRI events in Sensorimotor Motor Network using
Sparse Paradigm Free Mapping and Activation Likelihood
Estimates**

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1 **Decoding fMRI events in Sensorimotor Motor Network using Sparse Paradigm Free**
2 **Mapping and Activation Likelihood Estimates**

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7 **ABSTRACT**
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9 18 Most fMRI studies map task-driven brain activity using a block or event-related paradigm. Sparse
10 19 Paradigm Free Mapping (SPFM) can detect the onset and spatial distribution of BOLD events in
11 20 the brain without prior timing information; but relating the detected events to brain function
12 21 remains a challenge. In this study, we developed a decoding method for SPFM using a
13 22 coordinate-based meta-analysis method of Activation Likelihood Estimation (ALE). **We defined**
14 23 **meta-maps of statistically significant ALE values that correspond to types of events and**
15 24 **calculated a summation overlap between the normalized meta-maps and SPFM maps. As**
16 25 **a proof of concept, this framework was applied to relate SPFM-detected events in the**
17 26 **Sensorimotor Network (SMN) to six motor function (left/right fingers, left/right toes,**
18 27 **swallowing and eye blinks). We validated the framework using simultaneous**
19 28 **Electromyography-fMRI experiments and motor tasks with short and long duration, and**
20 29 **random inter-stimulus interval.** The decoding scores were considerably lower for eye
21 30 movements relative to other movement types tested. The average successful rate for short and
22 31 long motor events was $77 \pm 13\%$ and $74 \pm 16\%$ respectively, excluding eye movements. We
23 32 found good agreement between the decoding results and EMG for most events and subjects,
24 33 with a range in sensitivity between 55 and 100%, excluding eye movements. The proposed
25 34 method was then used to classify the movement types of spontaneous single-trial events in the
26 35 SMN during resting state, **which produced an average successful rate of $22 \pm 12\%$. Finally,**
27 36 **this paper discusses methodological implications and improvements to increase the**
28 37 **decoding performance.**
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41 Keywords: Functional MRI, decoding, meta-analysis, Activation Likelihood Estimation, Paradigm
42 Free Mapping.
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46 INTRODUCTION

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48 Resting state functional MRI (fMRI) data has been shown to contain signatures of brain activation
49 relating to 'spontaneous events' or uncued tasks performed by the subject and recently various
50 techniques have been developed to detect these activations (Liu et al., 2013, Smith et al., 2012,
51 Gaudes et al., 2011, Petridou et al., 2013, Caballero Gaudes et al., 2013, Karahanoglu et al.,
52 2013, Cisler et al., 2014, Chen et al., 2015, Allan et al., 2015). It remains a major challenge to
53 interpret spontaneous events in terms of brain function. Brain decoding enables us to relate
54 detected brain activity to a specific mental state (Tong and Pratte, 2012). In recent years,
55 machine learning algorithms have been applied to fMRI brain decoding (O'Toole et al., 2005,
56 O'Craven and Kanwisher, 2000, Haxby et al., 2001, Cox and Savoy, 2003, Haynes and Rees,
57 2005, Kamitani and Tong, 2005, Horikawa et al., 2013, Schrouff et al., 2012b). However, such
58 algorithms typically require the acquisition of a training dataset involving similar experimental
59 conditions to those that are to be subsequently decoded.

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61 An alternative approach is to decode fMRI data based on meta-analyses formed from prior fMRI
62 studies, combining data across different experimental methodologies and parameters (Poldrack,
63 2006), a process known as reverse inference. This approach has the advantage that it can
64 provide information on a large range of brain functions, which is particularly important when
65 decoding spontaneous events of unknown origin. It has been argued that such reverse inference
66 can have predictive power for a given mental process if a brain region is actively engaged
67 (Poldrack, 2006, Poldrack, 2011), by also taking account of task-setting in which the brain
68 activation occurred as well as existing meta-analysis databases (Hutzler, 2014). However,
69 reverse inference of spontaneous events is particularly challenging since the prior probability of
70 these events is unknown, i.e. decoding is difficult if we have no prior information about what
71 occurred during the data acquisition.

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73 The aim of this study was to decode task-induced and spontaneous events using Sparse
74 Paradigm Free Mapping (SPFM) and meta-analysis. We used SPFM to detect short (3 s) and
75 long (10 s) events in fMRI data without prior information on the timing of any movement or task
76 by using a regularized estimator that deconvolves the fMRI voxel time series assuming a
77 canonical haemodynamic response function (Caballero Gaudes et al., 2013, Petridou et al.,
78 2013). We then derived a decoding score relating detected patterns of motor activity to Activation
79 Likelihood Estimation (ALE) obtained from meta-analysis of task-based fMRI studies (Turkeltaub
80 et al., 2002, Laird et al., 2005). We validated the method by decoding events associated with
81 known responses to a set of six motor movements of short and long duration collected with
82 concurrent electromyography (EMG) recordings. We then used this method to determine the type

of spontaneous movements (within a predefined set of possible movements) undertaken during the period of a resting state fMRI acquisition acquired in the same experimental session.

THEORY

The following section outlines the use of Sparse Paradigm Free Mapping to detect events, and the formation of meta-maps and subsequent decoding of the fMRI data.

(i) Sparse Paradigm Free Mapping (SPFM) for fMRI analysis

Events can be detected within an fMRI dataset using Sparse Paradigm Free Mapping (SPFM), which requires no prior information on their timings. SPFM deconvolves the fMRI signal based on a linear haemodynamic model of the BOLD events using L1-norm regularized regression to give an SPFM activation map for each time frame in the fMRI data series (Caballero Gaudes et al., 2013, Petridou et al., 2013).

(ii) Formation of meta-maps

A meta-map characterizes convergence between the results of different studies and provides a probabilistic atlas of brain function in response to a particular task, which allows us to infer whether activation in a given voxel is likely to be related to a particular task.

Meta-maps can be formed using the Activation Likelihood Estimation (ALE) method implemented in GingerALE Version 2.3 (available at <http://brainmap.org/ale/index.html>) (Eickhoff et al., 2012, Eickhoff et al., 2009, Turkeltaub et al., 2012). The coordinate of brain activation due to a particular task, reported in a particular study considered in the meta-analysis, is known as a 'focus' (Laird et al. 2005). To allow for the uncertainty in the position of the focus due to factors such as inter-subject variability and imperfect anatomical alignment, the probability distribution of the location of the focus is modelled as a 3D Gaussian distribution centered on the focus. Let F_i be the event that any of the foci of activation in response to a particular task from the i^{th} study included in the meta-analysis occurs in the j^{th} voxel, such that $P(F_i)_j$ is the probability that a focus from the i^{th} study occurs in voxel j . If X studies are now considered in the meta-analysis, the probability that a focus from any of the studies occurs in the j^{th} voxel is known as the Activation Likelihood Estimation (ALE) value and is given by the union of all the $P(F_i)_j$, assuming that the results of all the studies are independent (Laird et al., 2005). For example, if there is one focus of activation and the ALE value for the j^{th} voxel is $P(F)_j=0.01$, there is a 1% chance that the focus from any of the studies included in the meta-analysis lay within the j^{th} voxel. A larger ALE value implies that there is a greater chance that one of the foci from the contributing studies lay in that voxel, and so one can infer a higher degree of association between that voxel and the relevant task.

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3 121
4 122 In this study, we defined a meta-map as a map of statistically significant ALE values for a
5 123 particular task, normalized to allow comparison between different tasks. The number of meta-
6 124 maps considered, M , determined the number of tasks that could be decoded. Table I shows the
7 125 $M = 6$ movement task meta-maps considered in this study, together with the total number of
8 126 voxels with significant ALE values and the range of significant ALE values for each meta-map.
9 127 Table II shows the overlap between the different meta-map regions. Since the number of studies
10 128 used to generate each meta-map differed, each meta-map had a different maximum ALE value.
11 129 This arbitrary difference between ALE values must be overcome in order to use the meta-maps
12 130 for decoding. Therefore, we normalized each meta-map by the sum of all voxel values within it, to
13 131 yield a normalized ALE value:

$$\alpha(F)_{j,m} = \frac{P(F)_{j,m}}{\sum_1^J P(F)_{j,m}} \quad \text{[Equation 1]}$$

12 132
13 133 where J is the total number of voxels in the m -type meta-map and $P(F)_{j,m}$ is the ALE value of
14 134 voxel j in the m -type meta-map. This normalized ALE value ensured that the probability across a
15 135 meta-map summed to unity, and could be interpreted as the conditional probability of a focus
16 136 location being in voxel j given there was a focus in meta-map m .

17 137
18 138 (iii) Decoding of events

19 139 The normalized meta-maps could be used to decode events detected with SPFM at each time
20 140 frame by estimating a decoding score (D_m) that quantified the spatial overlap between an SPFM
21 141 activation map and the meta-map associated with the m^{th} movement type, where the
22 142 abbreviations used to indicate each movement type are indicated in parentheses in Table I. For
23 143 each fMRI time frame, a non-conservative region of interest (ROI) was defined by applying a low
24 144 z-threshold to the SPFM activation map. For each of the m meta-maps the normalized ALEs
25 145 were summed within that ROI to give an Overlap Summation score S_m :

$$S_m(z_T) = \sum_{j=1}^K \alpha(F)_{j,m} \quad \text{[Equation 2]}$$

26 146
27 147 where K was the total number of voxels in the ROI at a SPFM z-threshold z_T . This process was
28 148 repeated for sequentially increasing values of z_T within a typical range of SPFM activation z-
29 149 scores, to obtain values of S_m as a function of SPFM z-threshold. The maximum possible value
30 150 of S_m would be 1 (Equation 1), which can be interpreted as the probability of a focus from meta-
31 151 map m being fully contained within the ROI.

32 152
33 153 The decoding score for each meta-map, D_m , was then defined as the area under the curve of S_m
34 154 plotted against z_T :

$$D_m = \int_{z_{low}}^{z_{high}} S_m(z_T) dz_T \quad \text{[Equation 3]}$$

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156 where z_{low} and z_{high} were minimum and maximum limits of typical SPFM activation z-scores. A
 157 large D_m indicated a large overlap between the SPFM ROI and areas of significantly high ALE
 158 value (convergence of foci on the m^{th} meta-map), and thus the SPFM event was likely to involve
 159 the task related to that meta-map. Integrating S_m in this way overcame the need to choose a
 160 particular threshold, whilst ensuring that a high D_m occurred when the SPFM map overlapped the
 161 meta-map across a reasonable range of thresholds. D_m was then converted to a normalized
 162 decoding z-score:

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$$Z_m = \frac{D_m - \mu_{Dm}}{\sigma_{Dm}} \quad \text{[Equation 4]}$$

164 where μ_{Dm} and σ_{Dm} were the mean and standard deviation of D_m across all time frames for the m
 165 meta-map. False Discovery Rate (FDR) correction was then performed ($q < 0.05$), where the
 166 total number of hypotheses was the number of time points multiplied by the number of meta-
 167 maps.

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169 This process resulted in M FDR-corrected, time series of decoding z-scores Z_m ($m = 1, \dots, M$).
 170 Significant values of Z_m could then be ranked, with the highest rank value of Z_m corresponding to
 171 the most likely task type (if any) at each time point.

172

173 **METHODS**

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175 The study was approved by the local Ethics Committee, and all subjects gave informed consent.
 176 Nine subjects participated, but datasets from two subjects were discarded due to incomplete data
 177 collection. The scan session included (i) short and long motor task fMRI paradigms for validation
 178 of the decoding method; (ii) resting state data for spontaneous event decoding assessment.

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180 Paradigm

181 Motor tasks were used to validate the decoding method due to the high specificity of the
 182 Sensorimotor Network (SMN) resulting from the nature of its cortical organization (Penfield and
 183 Rasmussen, Penfield and Boldrey, 1937). These tasks involved six motor movements:
 184 movement of right or left toes (contraction of all toes of the foot), movement of right or left fingers
 185 (thumb brushed against the tips of the rest of the fingers from little finger to first finger with the
 186 hand palm facing down), eye blinks and swallowing. Subjects were instructed to perform these
 187 movements with minimal head motion.

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4 189 Each MR session consisted of two paradigms: RUN1 (resting state and short task scan) and
5 190 RUN2 (long task scan), chosen to test the algorithm in different conditions and illustrated in
6 191 Figure 1(a). RUN1 consisted of a 5 minute resting state period followed by 10 minutes in which
7 192 short motor movements were performed. During the resting state period, a blank screen was
8 193 displayed and the subjects were instructed to keep their eyes open. Fifteen seconds before the
9 194 motor movement task paradigm began a “GET READY...” text was displayed on the screen. A
10 195 simple text instruction was then displayed indicating which movement was to be performed (e.g.
11 196 “R FOOT”). This was followed by a 3 second countdown display and then a red dot flashed 3
12 197 times at 1 second intervals. Subjects were instructed to perform each movement task with every
13 198 flash of the dot, except for the swallowing condition for which one movement was performed
14 199 within the 3 second interval. A white fixation-cross then appeared for a random inter-stimulus
15 200 interval of 18-24 seconds before the next movement instruction was displayed. This cycle was
16 201 repeated twenty-four times (four trials of each movement type) within the 10 minute period.
17 202 RUN2 consisted of 1 minute when a fixation cross was displayed, followed by 4 minutes of long
18 203 motor movement tasks and then a further 1 minute of fixation cross. In RUN2 each movement
19 204 type was performed continuously for a longer 10 second period (red dots flashed 10 times at 1
20 205 second interval) and swallowing movements were performed twice within the 10 second interval.
21 206 Only a single repeat was performed for each movement type in RUN2, and the inter-stimulus
22 207 interval varied randomly between 28-32 seconds.
23 208

24 209 Surface electromyography (EMG) was recorded throughout to detect muscle activity during the
25 210 tasks. MR-compatible electrodes were placed on the arms (on left and right extensor digitorum)
26 211 and legs (across the lower peroneus longus); these electrodes formed bipolar pairs, which were
27 212 fed into a MR-compatible bipolar amplifier [ExG amplifier, Brain Products, Munich, Germany], a
28 213 ground electrode was placed on the right elbow. A MR-compatible unipolar amplifier [MR-plus
29 214 amplifier, Brain Products, Munich, Germany] was used to measure muscle movement in the neck
30 215 and head simultaneously. Electrodes were placed above and below the center of the subject’s
31 216 pupil (frontalis and lower orbital orbicularis- right eye only (Blumenthal et al., 2005)), on the jaw
32 217 (masseter) and the right of neck midline to detect swallowing (approximately on the infrahyoid
33 218 (Vaiman et al., 2004)), with the reference electrode placed on the nose and the ground electrode
34 219 on the right mastoid bone. The electrodes were positioned to monitor the movements defined in
35 220 the meta-maps (see Table I). EMG data were recorded at a sample rate of 5 kHz with a
36 221 hardware filter set to record in the range 0.016-250 Hz with a roll-off of 30dB/octave at high
37 222 frequency. All electrodes impedances were kept below 25 k Ω and all electrode leads were
38 223 twisted to minimize wire loops and the consequential differential effect of the magnetic field on
39 224 the leads (van Rootselaar et al., 2007). The bipolar amplifier monitoring limb movement was
40 225 placed at the foot of the scanner bed, whilst the unipolar amplifier monitoring head movements

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3 226 was placed at the head of the scanner bed. Activity of platysma muscles on the neck could be
4 227 detected by the electrode on the neck (Vaiman et al., 2004), whilst swallowing movements could
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6 228 be distinguished by their distinctive EMG waveform.
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9 230 MR Data Acquisition

10 231 Data was acquired on a Philips 7 Tesla Achieva scanner [Best, Netherlands] using a 32-channel
11 232 head coil [Nova Medical]. fMRI data was acquired using axial gradient echo EPI (FOV=208 x 192
12 233 x 84 mm, voxel size =2 x 2 x 3 mm³, 28 slices, TE=25 ms, TR=1.5 s, flip angle=64°, SENSE
13 234 factor 3). To minimize head movements, foam pads were used to constrain the subjects' heads
14 235 within the head coil. During each fMRI scan, a Vectorcardiogram (VCG) and peripheral pulse unit
15 236 were used to record the cardiac trace (whichever signal had best quality was used in analysis)
16 237 and a pneumatic belt placed around the chest was used to record respiratory signals. These
17 238 signals were collected to allow for physiological noise correction of the fMRI datasets and surface
18 239 electromyography traces. Following the fMRI data acquisition, a three-dimensional, 1 mm
19 240 isotropic high resolution T₁-weighted MPRAGE scan and T₂*-weighted spoiled-FLASH scan were
20 241 acquired.
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23 243 Data Analysis

24 244 EMG data were analyzed using BrainVision Analyzer2 [Brain Products, Munich, Germany].
25 245 Gradient and pulse artefact corrections were performed using the average artefact subtraction
26 246 technique (Allen et al., 2000, Allen et al., 1998). The gradient artefact was corrected on all
27 247 channels using a sliding window containing 61 volume averages. Pulse artefact correction was
28 248 performed for the electrodes on the head and neck. The VCG was used to identify the R-peak of
29 249 the cardiac cycle (Debener et al., 2008, Mullinger et al., 2008, Allen et al., 2000, Allen et al.,
30 250 1998) and a sliding window of 21 averages was employed in the pulse artefact correction.
31 251 Absolute differences between active electrode pairs placed on arms, legs, the frontalis and lower
32 252 orbital orbicularis (for eye movements), and jaw and neck (for swallowing movements) were
33 253 computed to obtain a single EMG recording to monitor each limb, eye movements and
34 254 swallowing. The EMG traces were converted to z-scores in MATLAB, and data points with
35 255 amplitude more than twice the standard deviation of the mean (z-score ≥ 4) were inspected to
36 256 ensure that they had the appropriate waveform for an EMG trace (to exclude residual gradient
37 257 artefacts, etc.). The swallowing trace was analyzed by visual inspection since a particular
38 258 waveform corresponded to swallowing (as opposed to head movement). Markers were manually
39 259 placed on peaks that reflected both task-related and potential non-task related movements. The
40 260 final results were visually inspected to discount false positives that could arise from spikes in the
41 261 traces due to global movements.
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3 263 Figure 1 (b) summarizes the fMRI data analysis steps. fMRI datasets were realigned [SPM8]
4 264 (<http://www.fil.ion.ucl.ac.uk/spm/software/spm8/>), physiological noise corrected using
5 265 RETROICOR (Glover et al., 2000), spatially smoothed with a 4 mm isotropic Gaussian kernel,
6 266 and low frequency drift corrected up to and including third order fitted polynomials. The effects of
7 267 signal changes due to sudden head movements were excluded by generating null regressors of
8 268 those time points with $|d'| > 0.5$ mm/scan where $|d'|$ is the absolute derivative of the net
9 269 displacement vector from the translational parameters of the realignment procedure (Lemieux et
10 270 al., 2007).
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16 272 To increase computational efficiency, each participants' fMRI data was analyzed in four sections:
17 273 R1 (5 minute rest (resting state), scan dynamics 1-200 of RUN1), M1 (first 5 minutes of short
18 274 movement task, scan dynamics 201-400 of RUN1), M2 (second 5 minutes of short movement
19 275 task, scan dynamics 401-642 of RUN1) and M3 (long task, all scan dynamics of RUN2). Voxel-
20 276 wise mean correction was performed to compute percentage signal change. Voxels with variance
21 277 in the top 0.5 percentile were excluded from further analysis, since these voxels tend to be
22 278 related to draining veins. SPFM was performed on the datasets, using the 3dPFM function in
23 279 MATLAB (now available in AFNI (NIH/NIMH),
24 280 http://afni.nimh.nih.gov/pub/dist/doc/program_help/3dPFM.html), using L1-norm Dantzig selector
25 281 regularization path with Bayesian Information Criterion (BIC) for model selection. This produced
26 282 an Activation Time Series (ATS) indicating time points corresponding to events for every voxel.
27 283 Realignment parameters along with their Volterra expansion and null regressors (if any) were
28 284 included as additional covariates (Caballero Gaudes et al., 2013). ATS outputs from SPFM were
29 285 converted into a time course of maps of Z-scores. The SPFM output was then visually inspected
30 286 to exclude any time frames that showed strong artefacts at the edges of the brain and brief whole
31 287 brain activations (assumed to be motion or residual respiratory artefacts not removed by previous
32 288 procedures).
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42 290 Creating Meta-maps and Decoding

43 291 Meta-maps for each of the six movement types were created from a meta-analysis of 77 fMRI
44 292 studies of the eye (n=24) mouth (n=18), hand (n=21), and foot (n=14) movements (Table I) using
45 293 the BrainMap Sleuth Version 2.0 (BrainMap, <http://www.brainmap.org/sleuth/>) (see Supporting
46 294 Information Tables I-IV). Voxel-wise ALE values were computed for each movement type, and
47 295 these ALE maps were then thresholded using cluster-level inference correction (Eickhoff et al.,
48 296 2012). First, a cluster-forming threshold was chosen (uncorrected $p=0.001$). For this threshold, a
49 297 null distribution of cluster sizes was simulated from 5000 experiments selected at random from
50 298 the BrainMap database, with the same smoothness as the movement being considered (same
51 299 number of subjects, and same number of foci). ALE values were computed on the foci from this
52 300 random set of experiments and the cluster-forming threshold was applied. The resulting cluster
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3 301 sizes were recorded and the process was repeated to produce a null distribution of cluster sizes.
4 302 All cluster size values were used in each randomization run. A cluster-level inference threshold of
5 303 $p=0.01$ was then chosen to determine whether each cluster in the ALE maps was obtained by
6 304 chance. All ALE computations and cluster level inference correction were performed using
7 305 GingerALE Version 2.3 software (BrainMap, <http://www.brainmap.org/ale/>) (Eickhoff et al., 2012,
8 306 Eickhoff et al., 2009, Turkeltaub et al., 2012). The meta-maps were then normalized (see Theory
9 307 section). The Supplementary Motor Area (SMA) is commonly active in all meta-maps involving
10 308 sensorimotor tasks, and so to increase functional specificity between the six movement meta-
11 309 maps, the SMA was masked-out from the ROIs using the SMA mask from the Harvard-Oxford
12 310 cortical atlas available in FSL (FMRIB, <http://fsl.fmrib.ox.ac.uk/fsl/>).

13 311
14 312 The decoding z-score Z_m (see Equation 4 in Theory section) was calculated for each meta-map
15 313 m , at each time point, using trapezoidal numerical integration implemented in MATLAB between
16 314 SPFM z-threshold limits in steps of $z=0.1$. We chose a non-conservative minimum limit $z_{low}=0.1$
17 315 and $z_{high}=6$ since these values were within the typical range of SPFM activation z-scores. Values
18 316 of $Z_m > 6$ resulted from residual movement artefacts and time frames with such artefact were
19 317 excluded from analysis. The resulting Z_m timecourses for each movement type m were FDR-
20 318 corrected ($q=0.05$). Significant decoding z-scores were used to rank the movements in terms of
21 319 probability of each having occurred at each time point, with the decoded movement type being
22 320 classified as that with the highest rank.

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24 322 For task-based paradigms, task stimulus timings and EMG traces were used to validate whether
25 323 the actual movement took place (task or spontaneous movements). A True Positive (TP) was
26 324 defined as occurring when the meta-map corresponding to the highest ranked Z_m matched the
27 325 movement type of the stimulus and was confirmed by the EMG trace. A False Negative (FN)
28 326 occurred when the decoding method reported the incorrect movement type (FN_{wrong}), or when Z_m
29 327 failed to decode any event (FN_{null}). **It is not possible to know whether events detected**
30 328 **without simultaneous activation in the EMG were actual False Positives since the EMG**
31 329 **could only ever record a limited number of movements (restricted by the number of**
32 330 **electrodes applied) so we defined these as potential False Positives (Table III).** Decoding
33 331 sensitivity was calculated as $TP/(TP+ FN)\%$. For resting state data, the decoding z-score of
34 332 detected spontaneous events was compared in a similar way to potential movements identified in
35 333 the EMG trace.

334 335 **RESULTS**

336 337 EMG data

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3 338 Upon visual inspection, EMG traces identified task movements cued by visual stimuli during the
4 339 entire recordings in all subjects, except for Subject 4 and Subject 6. In Subject 4, contact
5 340 between electrodes with skin surface at the eye, right foot and left foot became loose halfway
6 341 through the short task experiment, so for those periods the time at which the stimulus cue
7 342 occurred was used for validation purposes. In Subject 6, no significant EMG spikes were
8 343 detected for the first left foot movement and second left hand movement, suggesting that this
9 344 movement was omitted by the subject during the experiment.
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14 345 15 346 Motor Validation Task Data

16 347 Figure 2 shows example SPFM maps detected at a time corresponding to a short task movement
17 348 (visually cued swallowing also detected in EMG - Figure 2 (a)), and with no movement (no task
18 349 stimulus and no EMG spike detected - Figure 2 (b)). The SPFM activation clusters detected
19 350 during the swallowing task overlapped areas of significant Activation Likelihood Estimation (ALE)
20 351 values for mouth movements in the corresponding meta-map. During the period of no movement,
21 352 no activation was detected in the mouth movement meta-map ROIs (or indeed other motor
22 353 ROIs), although a small area of activation can be seen posterior to the motor areas. Figures 2 (c)
23 354 and 2 (d) plot the corresponding Overlap Summation score S_m (Equation 2) for the 6 movement
24 355 meta-maps and also list the decoding scores D_m , based on the area under each of the curves
25 356 (Equation 3). For short movement task, large activated regions with high z-scores were detected
26 357 by SPFM, resulting in high S_m values that persisted at higher SPFM z-threshold, particularly
27 358 when there was large overlap between the activation map and meta-map. In contrast, for the
28 359 period of no movement the values of the overlap summation S_m were small at low SPFM z-
29 360 threshold and decreased rapidly with higher SPFM z-threshold for all movement types, since less
30 361 activation was detected by SPFM.
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40 363 Figure 3 shows the time course of the decoding z-score Z_m for each meta-map and the
41 364 corresponding EMG z-score traces for the short motor tasks for Subject 1. Task-induced motor
42 365 movements were detected by EMG at the time of the visually-cued stimuli (indicated by dotted
43 366 red lines). Other spikes were detected sporadically in the EMG traces due to spontaneous (non-
44 367 task) movements or possible residual movements related to tasks due to close proximity of leads
45 368 leading to the EMG breakout box. Swallowing events are not as apparent in the EMG traces as
46 369 other movements, but they were detected by their distinctive waveforms, rather than by peaks in
47 370 the EMG amplitude. Peaks in the appropriate decoding z-score timecourse were generally
48 371 observed at the time of the visually cued stimulus for hand (LH and RH), foot (LF and RF) and
49 372 mouth (Mo) movements. For eye blinks (E), the decoding score Z_E failed to detect any task-
50 373 based movements. Two non-task-based swallowing movements were detected in the EMG
51 374 traces during the left foot and left hand motor tasks at scan dynamics 110 and 137 respectively
52 375 (green crosses). At these time points Z_{LF} and Z_{LH} had higher amplitudes than Z_{Mo} . Figure 4
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3 376 compares all decoding score with all tasks for all subjects. It can be seen that, excluding eye
4 377 movements, the highest ranked decoding score correspond to the correct (task) movement type.
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6 378 Peaks in the decoding z-score were also found that were neither task-related nor associated with
7 379 EMG, for example at time points 184 (LF), 240 (M) and 390 (M) for Subject 1.
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10 381 Table IV summarizes the validation results from all subjects for RUN 1 (short motor task). This
11 382 table shows that generally events were successfully decoded for hand, foot and mouth
12 383 movements across all subjects. Table IV (a) indicates how often the maximum meta-map
13 384 decoding score corresponded to a correct movement type. The average successful decoding
14 385 rate was $66 \pm 7\%$ averaging across all subjects and movement types ($77 \pm 13\%$ when eye
15 386 movements were excluded). The decoding rate was only $11 \pm 18\%$ for eye movements across
16 387 all subjects, for which all false negatives were due to no event being decoded (FN_{null}) (no
17 388 significant overlap between meta-map and activation). From Table IV (b), it is also apparent that,
18 389 besides Subject 3, most of False Negatives were FN_{null} , but hand movements had a higher
19 390 misclassification rate (FN_{wrong} greater than FN_{null}). Importantly for Subject 6, no significant EMG
20 391 spikes were detected for the first left foot movement and second left hand movement, suggesting
21 392 that this movement was not performed, the decoding results supported this finding since no foot
22 393 movement was decoded at these time points. Table IV (e) also shows the number of null
23 394 regressors included and suggests a relationship between decoding accuracy and lack of
24 395 movement artefacts. Spontaneous (non-tasked) movements were also detected by EMG (trace
25 396 not shown in Figure 4), and some of these were successfully decoded for Subject 3 (24%) and
26 397 Subject 4 (8%), Table V. There were also a number of decoded events that were not associated
27 398 to any stimuli or EMG traces (excluding eye movements), shown in Table IV (d), which could be
28 399 interpreted as false positives for the decoding but may be related to activity not detected by
29 400 EMG. **It is not possible to calculate Positive Predicted Value $[TP/(TP + FP)]$ since we
30 401 cannot confidently label detected events not associated with task or EMG as false
31 402 positives (FP), since the EMG is unable to detect all possible movements. However,
32 403 assuming that all potential false positives are actual false positives, the minimum Positive
33 404 Predicted value would be 77% (range 64-100%).**
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47 406 Figure 5 and Table VI summarize the results for RUN2 (long motor task). For Subject 1, at time
48 407 point 41 there was an increase in decoding score for all movement types, indicating possible
49 408 head movement that was not excluded by the null regressors (the absolute derivative of the net
50 409 displacement vector of translational head motion at that time point was $|d'|=0.41$ mm/scan). The
51 410 average successful decoding rate for the long task was $74 \pm 16\%$ excluding eye movements. In
52 411 contrast to the short movement task, most False Negatives in the long movement task were
53 412 attributed to misclassification (FN_{wrong}). **The minimum Positive Predicted value would be 47%**
54 413 **(range 30-83%).**
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415 For the resting state dataset, SPFM detected spontaneous events in the Sensorimotor Network
416 (SMN) that were not attributed to any given task. Asterisks indicate events that were found by
417 decoding and confirmed by EMG. Figure 6 illustrates the variation in the types and durations of
418 movement detected on EMG and decoded events between subjects in the resting state. The
419 meta-maps overlaid on the SPFM maps for corresponding decoded events, corresponding to
420 particular movements detected by EMG at rest for Subject 1 are also shown at the top of Figure
421 6. Table VII (a) shows the fraction of spontaneous events for which the decoding agreed with the
422 movement simultaneously detected on EMG. Table VII (b) summarizes spontaneous events that
423 were detected at rest with significant decoding score, but which were not associated with any
424 event detected by EMG.

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426 **DISCUSSION**

427 We have demonstrated a method for decoding movement events in fMRI data with no prior
428 knowledge of the nature of the movement and without using training data sets. Instead, we used
429 Activation Likelihood Estimation and coordinate based meta-analysis. The decoding ranks the
430 potential decoded movements at each time point, with the highest rank taken as the most
431 probable movement type. We have validated the method on both long and short movement
432 tasks, and have also shown that it can decode spontaneous activity occurring in resting state
433 data.

434 There has been substantial development in fMRI brain decoding in recent years involving visual
435 perception, visual features, visual objects, novel visual scenes, attention processes, imagery and
436 working memory, episodic memory, semantic knowledge and phonological representations (Tong
437 and Pratte, 2012). Most of these methods use machine learning algorithms such as Support
438 Vector Machines (SVM) to train a classifier to recognize spatial patterns in order to decode.
439 Several studies have applied machine learning algorithms to decode non-task brain activity by
440 building a classifier based on tasks. Schrouff et al. utilized machine learning (Gaussian
441 Processes classifier) trained on three mental imagery tasks to access activity during rest periods
442 before and after tasks (Schrouff et al., 2012a, Schrouff et al., 2012b). Although the results
443 suggested that classification of resting state sessions can be performed by applying previously
444 trained classifiers, this method is limited to the number of categories the decoder is trained for.
445 Although our method is also limited to the number of meta-maps considered, it is easier to
446 extend it by generating meta-maps for more categories from a large database of literature,
447 compared to reconstructing new experiments to train the decoder. The concept of decoding
448 using meta-analysis is supported by the availability of large-scale automated meta-analysis of
449 fMRI data. *Neurosynth* (NIH, <http://neurosynth.org/>) (Yarkoni et al., 2011) measures similarity
450 between a spatial activation map (such as T-map obtained using General Linear Models

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3 451 analysis) and patterns associated with 'cognitive maps' available in its database using a spatial
4 452 correlation (Pearson correlation). To our best knowledge, no method has been developed to
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6 453 decode spontaneous events quantitatively by means of voxel-wise coordinate-based meta-
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8 454 analysis measures and without prior experiments undertaken by the subject being investigated.

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10 455 Depending on computational resources available, the method described is potentially time
11 456 consuming to implement and run, but has the potential to provide unique information about
12 457 behavior in the resting state, and separating of distinct behaviors from other brain activity. This
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14 458 could be useful in many ways, for instance, in clinical research studying somatic pain in
15 459 conditions such as irritable bowel syndrome, or in psychological research in naturalistic
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17 460 paradigms or into emotional congruence.

18 19 461 Validation

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21 462 We validated the technique using task-based data where the movement was confirmed by EMG.
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23 463 The decoding method was validated against 24 short task movement trials (3 seconds duration
24 464 with 1 movement performed per second for each trial), and also against spontaneous events
25 465 (which are inevitably quite sparse). We found good agreement between decoding results and
26 466 EMG for most events and subjects, with a range in sensitivity between 55 and 100% excluding
27 467 eye movements. The sensitivity was lowest for Subject 3, probably related to the fact that this
28 468 subject showed more motion. Across all subjects, only 11% of short eye movement tasks were
29 469 successfully detected (high FN_{null}), probably because of the smaller BOLD signal in response to
30 470 eye movements, which may be because eye blinks are very common movements that involve a
31 471 smaller muscle volume compared to many other movements. Furthermore, there is a lack of
32 472 fMRI literature on eye blinks, so that the studies included in the eye movement meta-map were
33 473 predominantly eye saccades, which will not have been ideal for decoding eye blinks. This
34 474 illustrates that decoding can only be achieved reliably if appropriate metamaps are available.

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36 475 During any tasked movement, the decoding score was largest for the meta-map corresponding to
37 476 the movement being undertaken, but also tended to increase for other movement types. This
38 477 may be due to overlap between the meta-maps (shown in Table II) or because activation was not
39 478 confined to the region of a single meta-map during a particular movement. This could indicate a
40 479 lack of selectivity in the brain's response to a particular behavior, or functional connectivity within
41 480 the SMN that is activated as a whole during a given movement (Biswal et al., 1995), although the
42 481 SMA was masked out during the analysis to increase specificity to different motor activations.
43 482 Alternatively, it could be due to imperfect registration of meta-maps to the subject's data space or
44 483 subject anatomical variability.

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48 485 Events may not have been decoded successfully, either because no activation was detected by
49 486 SPFM or because the activation did not adequately overlap the appropriate meta-map. One
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3 487 problem with the validation was that although we detected unexplained events (peaks in the
4 488 decoding traces that were not detected by EMG - potential false positives), it was impossible to
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6 489 determine if these were actual false positives and hence specificity. Some such peaks are
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8 490 always expected since the EMG electrodes were placed at specific muscle locations, and thus
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10 491 not sensitive to all types of movements included in the meta-analysis; the proposed decoding
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12 492 method might provide the only means of interpreting such spontaneous activations. Nonetheless
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14 493 for Subject 6 where no EMG events were detected corresponding to tasked short movements,
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16 494 the method also decoded no movements, strongly suggesting that no movement was actually
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18 495 performed by the subject. The EMG setup was carefully designed to minimize artefacts due to
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20 496 the MRI environment, in particular limiting movement of the electrode leads when the subjects
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22 497 performed a movement. Nonetheless, visual inspection of the thresholded EMG traces showed
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24 498 that some residual lead movements were still picked up by nearby EMG channels (Figure 3).
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26 499 Further validation work would be simplified if movements could be automatically detected in the
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28 500 EMG trace, either by detecting non-periodic perturbations in the traces, or by pattern recognition
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30 501 of waveform patterns in a sliding window approach.

31 502 Spontaneous events

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33 503 Although the term “resting state” is usually interpreted as no task being undertaken, in reality the
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35 504 brain is always actively performing tasks involving internal or external thoughts, or movements
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37 505 (Binder et al., 1999). Here we confirmed our previous finding that some spontaneous events in
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39 506 the Sensorimotor Network are in fact spontaneous movements as detected by EMG (Petridou et
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41 507 al., 2013). We have previously suggested that functional connectivity is somewhat driven by such
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43 508 spontaneous BOLD events (Allan et al., 2015, Petridou et al., 2013). To what extent these
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45 509 spontaneous events may cause differences in connectivity due to inter-subject or inter-group
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47 510 behavior variability is of great interest but still unknown.

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49 511 Non-tasked movements that occur at rest are often shorter and smaller than task-induced
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51 512 movements, generally causing weaker fMRI activations of smaller spatial extent, and thus
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53 513 insignificant decoding scores. Similarly non-tasked movements also produce lower EMG scores
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55 514 particularly since the EMG was probably not set up to detect the exact spontaneous movement
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57 515 being undertaken. **These reasons will have led to, spontaneous events being less likely to**
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59 516 **be detected, decoded, and confirmed by EMG.** However, we expect that faster sampling of
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517 fMRI data, for instance using simultaneous multi-slice imaging (Feinberg et al., 2010, Moeller et
518 al., 2010), will provide significantly increased sensitivity to improve decoding. **Furthermore, the**
519 **underlying SPFM algorithms are designed to enforce sparsity in the number of events, but**
520 **this might be relaxed particularly since the final statistical test for the decoding is much**
521 **more stringent since it is based on the pattern of activation rather than a single voxel time**
522 **course.** Some spontaneous events were detected in resting state data with significant decoding
523 score, but were not associated with any event detected by EMG. At this stage it is impossible to

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3 524 know whether these events relate to spontaneous movements, reflect such lack of sensitivity in
4 525 EMG, or reflect some other underlying spontaneous activity in the SMN, such as motor imagery
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6 526 or planning of action (Mizuguchi et al., 2014).
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8 527 In principle, this approach could be extended to study non-motor brain functions by including
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10 528 metamaps for a wider range of tasks, but this will pose a number of challenges. Firstly, the
11 529 signals are sometimes smaller in the non-motor networks making detection and decoding more
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13 530 difficult. Secondly, the validation will be more complicated if there is no overt response involved,
14 531 this might be addressed controlling the state of a subject (e.g. in naturalistic paradigms such as
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16 532 watching a movie) (Hasson et al.).
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18 533 Methodology

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20 534 **This section discusses the methodology implications and improvements that can be**
21 535 **made to increase the decoding performance in more detail.** The TR was 1.5s, limiting the
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23 536 temporal resolution of the data set. Therefore, the 3 events occurring in the short paradigm or the
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25 537 10 events occurring in the long paradigm could not be separated, although the individual events
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27 538 were apparent in the EMG trace. Despite the temporal blurring of the hemodynamic response,
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29 539 we predict that increased temporal resolution, for instance by using simultaneous multi-slice
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31 540 imaging (Feinberg et al., 2010; Moeller et al., 2010), would help to differentiate between
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33 541 individual movements within blocks, in addition to enhancing the performance of the SPFM
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35 542 deconvolution, and consequently the decoding accuracy. This can be pursued in future as fast
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37 543 fMRI sequences become more routinely available.

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39 544 The proposed technique depends on the success of SPFM in detecting events. The combination
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41 545 of the L1-norm (sparse regression) and Bayesian Information Criteria model selection in SPFM
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43 546 controls the number of false positives for event detection (Caballero Gaudes et al., 2013).
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45 547 However, fMRI datasets that are corrupted by large motion artefacts and physiological noise may
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47 548 still have residual noise even after standard motion and physiological noise corrections. In this
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49 549 study, we included six translational motion regressors with their Volterra expansion as regressors
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51 550 for SPFM (Lemieux et al., 2007), and omitted voxels that displayed high variance which were
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53 551 probably due to draining vein artefacts. We also excluded frames by using null regressors where
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55 552 the displacement vector was greater than 0.5 mm per scan and visually scrutinized the SPFM
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57 553 results to exclude time frames that were suspected of containing other artefacts. Alternatively,
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59 554 other methods based on ICA decomposition and the identification of artefactual independent
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61 555 components, such as FIX (Griffanti et al., 2014, Salimi-Khorshidi et al., 2014) or AROMA (Pruim
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63 556 et al., 2015a, Pruum et al., 2015b), or more sophisticated tissue-based nuisance regression such
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65 557 as ANATICOR (Jo et al., 2010, Jo et al., 2013) could be explored to further reduce artefacts and
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67 558 physiological noise from the fMRI data. For the long task (RUN 2), the decoded activations did
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69 559 not extend through the entire stimulus duration (Figure 5). In future work, more sophisticated
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3 560 SPFM algorithms using a structured L1-norm regularization, such as Fused Lasso or Smooth
4 561 Lasso (Caballero-Gaudes et al., 2012, Hernandez-Garcia and Ulfarsson, 2011) could provide a
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6 562 more accurate deconvolution for prolonged and intermixed stimuli than the Dantzig Selector,
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8 563 potentially improving decoding accuracy.

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10 564 The method also depends on the accuracy of meta-maps, how well they correspond to the tasks
11 565 being undertaken, and the overlap between them. The failure to decode eye movements in this
12 566 study highlights that it is essential for studies used in the meta-analysis to be as similar as
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14 567 possible to the movement type to be decoded. The proposed decoding methodology required
15 568 maps of expected patterns of activation in response to particular behaviors and for this it uses
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17 569 meta-analysis of many fMRI studies, rather than subject-specific data, although ALE attempts to
18 570 account for intersubject variance by modelling the location of the activation as a Gaussian
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20 571 distribution. Using datasets acquired from the subject under investigation would increase the
21 572 sensitivity by providing better overlap between the SPFM and meta-maps matching the subject's
22 573 anatomy. This might particularly benefit the decoding of more subtle activations seen in the
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24 574 resting state. However, this would greatly reduce the usefulness of the technique, as it would
25 575 require all activations of interest to be mapped prior to the decoding experiment for each subject,
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27 576 rather than building on the expanse of fMRI literature. Increasing the number of studies used in
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29 577 the meta-analysis might also increase the accuracy of ALEs. An alternative approach is to
30 578 integrate SPFM results with *Neurosynth* (NIH, <http://neurosynth.org/>), a platform that synthesizes
31 579 activation results from many different fMRI studies (Yarkoni et al., 2011).

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34 580 Meta-analysis works well in Sensorimotor Network due to the high selectivity of its cortical
35 581 organization with limited overlap between activated regions for different motor tasks (Penfield
36 582 and Rasmussen, Penfield and Boldrey, 1937, Schott, 1993). Here we developed a method of
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38 583 increasing selectivity by masking out the SMA region common to all movement tasks, and further
39 584 masks could be applied to focus on smaller activated areas (e.g. to decode which finger was
40 585 being moved (Sanchez-Panchuelo et al.)). Conversely, if the aim were to separate primary types
41 586 of activation (e.g. visual and motor), then the mask over the SMA could be removed. Extending
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43 587 the decoding method to cognitive resting state networks may be challenging since there is less
44 588 functional selectivity in the relevant activation maps, which might thus reduce the likelihood of a
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46 589 valid reverse inference (Hutzler, 2014, Poldrack, 2011).

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49 590 In developing this method, we explored several alternative methods of estimating the probability
50 591 that an activation area was related to a task. Simple binary conjunction between activation maps
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52 592 and meta-maps did not take into account the difference in z-score magnitudes of the SPFM and
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54 593 ALE values. Similarly, spatial correlation between activation and meta-maps was not appropriate
55 594 since meta-maps are built from Gaussian distributions around foci of activations, which do not
56 595 take account of the underlying shape of the pattern of activation in the individual studies, which
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58 596 are reflected in SPFM maps. Multiplying activation maps (z-scores) and meta-maps (via p-values
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3 597 converted to z-scores) together can produce a high product value either due to the activation, the
4 598 ALE or both, and these situations cannot be distinguished. Building a multivariate distribution
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6 599 from both the ALE z-scores and SPFM z-distribution was not appropriate because the joint
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8 600 distribution was generally biased along the axis of the SPFM distribution, making it impossible to
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601 define a simple confidence interval ellipse to detect outliers.

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11 602 The 'decoding z-score' developed here is a measure of overlap of SPFM spatial activations with
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13 603 the ALE meta-maps. An advantage of this approach is that it does not require a fixed threshold to
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15 604 be applied to SPFM z-scores, which is important since SPFM z-scores can vary significantly
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17 605 between scans, depending on fMRI data quality and inter-subject differences in BOLD response
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19 606 amplitude. The meta-maps were normalized to allow fair comparison between them. This
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21 607 normalization process assumes that behaviors corresponding to each of the M meta-maps are
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23 608 equally likely to occur in any given time frame. This is reasonable since each time frame is
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25 609 analyzed independently, which is fundamental to the concept of detecting and decoding
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27 610 spontaneous events. If the prior probability of certain events were known for some
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29 611 circumstances, the proposed **method could be adapted to consider this information.**

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31 612 **The decoding performance reported here is lower than that reported for decoding**
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33 613 **methods based on machine learning or Multivoxel Pattern Analysis (MVPA). However, to**
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35 614 **our knowledge, previous attempts at decoding based on MVPA have been constrained by**
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37 615 **the need to acquire training data at an individual level. The proposed method decodes**
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39 616 **data from one individual using a meta-analysis of fMRI data, i.e. acquired on other**
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41 617 **individuals and at other times and locations, trading decoding power for lifting the**
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43 618 **constraint of needing to acquired training data. Future work should investigate whether**
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45 619 **the combination of machine learning approaches with fMRI meta-analyses would give**
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47 620 **increased decoding power, although the overlap measures used here could still be used**
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49 621 **as a measure of the contribution of different behaviors to a particular event.**

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52 623 **CONCLUSION**

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54 624 To conclude, this work provides a novel method to decode events detected in fMRI data using
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56 625 Sparse Paradigm Free Mapping in combination with brain decoding based on meta-analysis.
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58 626 After validation in tasked motor movements, the proposed method has determined the nature of
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60 627 spontaneous movements undertaken in the apparent resting state, and we have confirmed these
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62 628 finding using EMG. These results underline our assertion that functional connectivity analysis of
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64 629 resting state data is inevitably affected by spontaneous and unpredictable behaviors. The
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66 630 decoding technique proposed here provides a means of interpreting such spontaneous activity. It
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68 631 is now necessary to determine the sensitivity of these methods to more subtle behaviors and
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70 632 responses.

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For Peer Review

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800 FIGURE LEGEND

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802 Figure 1 (a): Experiment paradigm of RUN1 and RUN2. RUN1 comprised a 5 minute rest period
803 followed by 10 minutes of short motor movement task (twenty-four 3-second motor task trials
804 performed separated by a random inter-stimulus interval (ISI) of 18-24 seconds). 3 movements
805 were done in each short task trial, with four trial repetitions of each movement type except for the
806 swallowing movement which was performed once. RUN2 comprised a 1 minute green fixation
807 cross, followed by a 4 minute long motor movement task (six 10-second motor task trials with
808 random ISI of 28-32 seconds), and then a further 1 minute of fixation cross. 10 movements were
809 done in each long task trial, except for swallowing movement which were performed twice, with
810 one trial repetition of each movement type. (b): Flow chart of decoding method. SPFM was
811 performed on pre-processed data from RUN1 and RUN2. Six meta-maps were generated for
812 each movement type using cluster-level inference in GingerALE. A decoding z-score, Z_m was
813 then computed for each meta-map m at each time point to quantify spatial overlap between
814 SPFM activation time frames and the m^{th} meta-map. All decoding scores were FDR-corrected
815 ($q < 0.05$).

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817 Figure 2: (a) Example SPFM map (red-yellow) for Subject 1 produced at time frame 154 of the
818 short task RUN1 during a swallowing condition of the movement task detected by EMG. The
819 SPFM map is overlaid on the corresponding meta-map (green). (b) SPFM map (red-yellow)
820 produced at time frame 10 of the short task RUN1 (no movement expected or detected by EMG)
821 overlaid on corresponding meta-map (green). (c) Overlap Summation score S_m for all movement
822 types for time frame 154. (d) Overlap Summation score S_m for all movement types for time frame
823 10. The decoding score, D_m , which is the area under each curves for (c) and (d), is given in
824 respective colors indicated in the legend.

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826 Figure 3: Decoding z-score Z_m (top row) and EMG z-score trace (bottom row) during short task
827 paradigm in Subject 1 for each movement type: eye (E), swallowing (Mo), left hand (LH), right
828 hand (RH), left foot (LF) and right foot (RF). Vertical dotted red lines indicate the times of the
829 visual-cue stimulus, and vertical dotted green lines indicate movement detected by EMG trace.
830 Horizontal aqua lines in EMG traces indicate $|z| > 4$. Spikes in mouth EMG traces are not as
831 apparent compared to other EMG traces because swallowing movements are reflected as
832 distinctive waveform patterns, rather than an amplitude of the signal. Two non-task-based
833 swallowing movement were detected by the decoding z-score at scan dynamic 110 and 137
834 (indicated by green cross), however Z_{LF} and Z_{LH} at these time points had higher magnitude than
835 Z_{Mo} .

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3 837 Figure 4: Decoding z-scores (FDR corrected, $q=0.05$) during short task for all subjects. The
4 838 colored bands indicate the tasked stimulus given to the subject. The colored lines show the
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6 839 decoding z-scores for each meta-map type. The movement type with the highest decoding z-
7 840 score is indicated by a colored square. The decoded movement types generally corresponded to
8 841 the correct task (matching colored bands and squares), except for eye movements.
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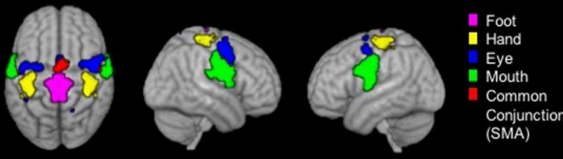
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11 843 Figure 5: Decoding z-score (FDR-corrected, $q=0.05$) during long task RUN2 for all subjects and
12 844 movement types. The colored bands correspond to the periods of the tasked stimuli and the lines
13 845 indicate the decoding scores. The colors corresponding to movement types displayed in the
14 846 legend. Peaks of the decoding z-score are denoted with squares in respective colors. The
15 847 movement type with the highest decoding score generally corresponded to visual-cued
16 848 movement condition (matching colored bands and squares), except for eye movements.
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19 850 Figure 6: Decoding z-score (FDR-corrected, $q=0.05$) for all movement types during 5 minutes
20 851 resting state for Subject 1 to 7. Spatial maps showing SPFM activations in z-score (red-yellow)
21 852 overlay on meta-maps for time frames for $n=7, 59, 88, 116,$ and 195 for Subject 1 are also shown
22 853 at the top of the figure. The colored bands indicate movement detected in EMG traces with the
23 854 movement type shown by the color in the legend. The colored lines show the decoding z-scores
24 855 for each meta-map type. The movement type with the highest decoding z-score is indicated by a
25 856 colored square. Asterisk (*) denotes decoded events that coincided with movements detected on
26 857 EMG traces.
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Table I: Details on meta-map for each of the six movement tasks: eye (E), mouth (M), left and right hand (LH and RH), and left and right foot (LF and RF). The number of studies used to form each meta-map is listed, together with the total number of significant ALE voxels, and maximum and minimum ALE range in each meta-map.

Meta-map



Movement Type	Eye (E)	Mouth (Mo)	Left Hand (LH)	Right Hand (RH)	Left Foot (LF)	Right Foot (RF)
No. of studies	24	18	21		14	
No. of significant ALE voxels	6208	6411	3870	3877	2014	2012
Maximum ALE (at centre of cluster)	0.063	0.050	0.054	0.005	0.046	0.044
Min ALE	$1.7 \cdot 10^{-8}$	$1.5 \cdot 10^{-9}$	$4.0 \cdot 10^{-10}$	$3.3 \cdot 10^{-9}$	$3.7 \cdot 10^{-9}$	$3.7 \cdot 10^{-9}$

Table II: Percentage overlap between meta-maps calculated as the overlap area divided by the number of voxels in region (b). The SMA was excluded from all calculations.

		PERCENTAGE OVERLAP BETWEEN META-MAPS, $[(a) \cap (b)] / (b)$					
(a) \ (b)	Eye	Mouth	Left Hand	Right Hand	Left Foot	Right Foot	
Eye	100.0	11.3	11.4	10.4	0.0	0.0	
Mouth	8.9	100.0	7.2	7.0	1.2	1.3	
Left Hand	17.7	14.2	100.0	0.0	2.1	0.0	
Right Hand	15.4	13.3	0.0	100.0	0.0	4.2	
Left Foot	0.0	6.3	5.6	0.0	100.0	8.6	
Right Foot	0.0	5.9	0.0	10.2	7.4	100.0	

Table III: Summarizing the classification of different events for the example of hand movements.

	No movement decoded in area expected from task or EMG	Movement decoded in area expected from task or EMG
EMG: No movement	Potential True Negative (pTN): Cannot be sure since EMG only monitors certain muscle locations	Potential False Positive (pFP): Cannot be sure since EMG only monitors certain muscle locations
EMG: Movement	False Negative: Decoding method either did not predict an event (FN_{null}), or decoded it incorrectly (FN_{wron})	True Positive (TP)

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Table IV: Events decoded in short movement task (RUN1). (a) Number of events where the highest decoding z-score rank corresponded with the visually-cued tasked movement and EMG, (*except Subject 4, where validation was used visually-cued tasked movement only for left and right foot). (b) Total number of false negatives due to a misclassification (FN_{wrong}) or no event detected (FN_{null}). (c) Success rate of decoded events averaged over all movement types, which describes the sensitivity of the decoding method. An event is successfully decoded when its highest rank of meta-map channel matches the visually-cued tasked movement and is confirmed by EMG. (d) Number of decoded events which were not associated with stimuli or EMG traces (potential false positives). (e) Total null regressors (time frames that had more than 0.5mm/scan displacement) that were included in the SPFM analysis. For subject 2, time frames $n=203$ to 208, which were during periods of rests, were also excluded due to artefacts.

SHORT TASK PARADIGM (TASK-BASED MOVEMENTS)										
Subject	(a) Number of events detected by decoding as a fraction of number expected by task and confirmed by EMG						Excluding eye movements			(e) Total Null Regressors
	Eye	Mouth	Left Foot	Right Foot	Left Hand	Right Hand	(b) Total False Negative (FN_{wrong} FN_{null})	(c) % decoded task events (sensitivity)	(d) Number of decoded events not associated with stimuli or EMG (pFP)	
2	2/4	4/4	4/4	4/4	4/4	4/4	0	100	5	5
3	0/4	0/4	4/4	4/4	1/4	2/4	9(8 1)	55	4	15
4	0/4	3/4	3/4*	2/4*	4/4	2/4	6(2 4)	70	8	5
5	0/4	2/4	3/4	3/4	3/4	4/4	5(1 4)	75	7	0
6	0/4	4/4	1/3	3/4	3/3	3/4	4(2 2)	77	0	10
7	1/4	3/4	3/4	2/4	4/4	4/4	4(0 4)	80	5	5
Total False Negative (FN_{wrong} FN_{null})	25 (0 25)	9 (3 6)	6 (1 5)	6 (0 6)	6 (4 2)	5 (4 1)				
% success rate averaged over all subjects	11	68	77	82	79	82				

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Table V: Spontaneous (non-task) events were decoded in the short movement task (RUN1) (highest ranked decoding z-score Z_m corresponds with correct spontaneous movement type in EMG trace). This table shows the number of events successfully decoded out of total number of events detected via EMG, excluding eye movements, and provides the best estimate of sensitivity for spontaneous events.

Subject	Number of successfully decoded events as a fraction of number of events detected via EMG (excluding eye movements)
1	0/3
2	0/3
3	4/17 (1 mouth, 3 Right Foot)
4	1/13 (1 mouth)
5	0/1
6	0/3
7	0/2

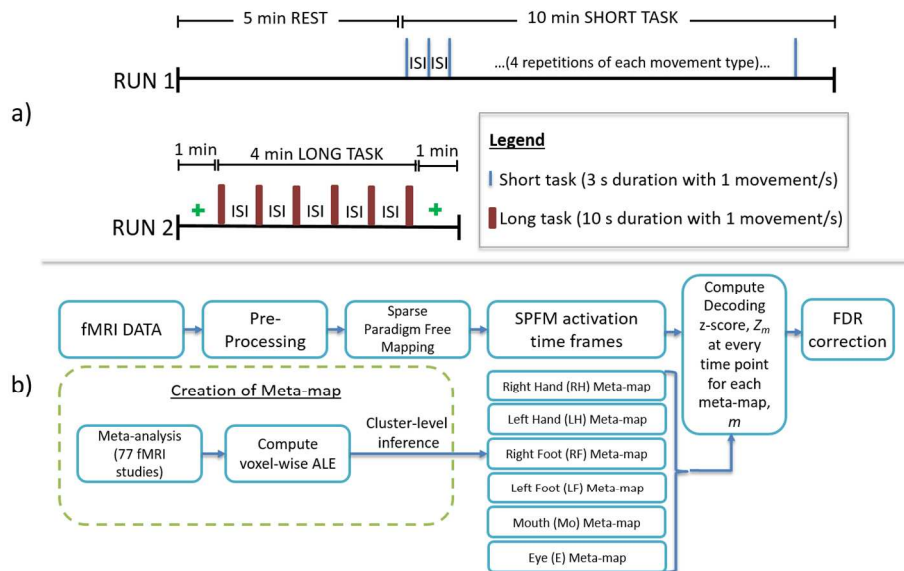
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Table VI: Events decoded in long movement task (RUN2). (a) Number of events successfully decoded in long task paradigm, which was verified using both stimuli markers and EMG. The expected total number of tasks perform per movement type is 1. (b) Total number of false negatives due to a misclassification (FN_{wrong}) or no event detected (FN_{null}). (c) Success rate of decoded events excluding eye movements (sensitivity). (d) Number of decoded events which were not associated with stimuli or EMG traces (potential false positives). (e) Total null regressors (time frames that had more than 0.5mm/scan displacement) that were included in the SPFM analysis. *For subject 1, 10 time frames were manually excluded from analysis due to residue artefact detected upon visual inspection (scan dynamic=24 to 27, 58 to 65). These time frames occurred during rest periods.

LONG TASK PARADIGM										
Subject	(a) Number of events decoded as a fraction of number expected by task and confirmed by EMG						Excluding eye movements			(e) Total Null Regressors
	Eye	Mouth	Left Foot	Right Foot	Left Hand	Right Hand	(b) Total False Negative (FN_{wrong} FN_{null})	(c) % decoded task events (sensitivity)	(d) Number of decoded events not associated with stimuli or EMG (pFP)	
1	0/1	1/1	1/1	0/1	1/1	1/1	1(1 0)	80	5	11*
2	0/1	1/1	1/1	1/1	0/1	1/1	1(1 0)	80	9	10
3	0/1	0/1	1/1	1/1	1/1	0/1	2(2 0)	60	6	9
4	0/1	0/1	1/1	0/1	1/1	0/1	3(0 3)	40	3	23
5	0/1	0/1	1/1	1/1	1/1	1/1	1(0 1)	80	3	0
6	0/1	1/1	1/1	1/1	1/1	1/1	0	100	1	0
7	0/1	1/1	1/1	0/1	1/1	1/1	1(0 1)	80	5	0
Total False Negative (FN_{wrong} FN_{null})	7 (0 7)	3 (1 2)	0	3 (1 2)	1 (1 0)	2 (1 1)				
% success rate averaged over all subjects	0	57	100	57	86	71				

Table VII: Events decoded in resting state (RUN1). (a) Number of successfully decoded events (highest ranked Z_m correspond with correct movement type in EMG trace) divided by the total number of movements detected in EMG. (b) Number of decoded spontaneous events which were not associated with stimuli or EMG traces. Eye movements were excluded for all tabulations. (c) Total null regressors (time frames that had more than 0.5mm/scan displacement) that were included in the SPFM analysis. *For subject 7, 6 time frames were manually excluded from analysis due to residue artefact detected upon visual inspection (scan dynamic, $n = 49$ to 54).

MOVEMENTS DURING RESTING STATE (excluding eye movements)			
Subject	(a) Number of spontaneous movements decoded and confirmed by EMG as a fraction of number expected by EMG	(b) Number of decoded events not associated with EMG trace	(c) Total Null Regressors
1	4/19 (3 mouth, 1 left hand)	8	9
2	1/2 (1 right hand)	5	0
3	4/32 (2 right foot, 1 left foot, 1 mouth)	1	0
4	2/12 (1 right hand, 1 mouth)	8	0
5	1/4 (1 mouth)	9	0
6	1/7 (1 right hand)	7	5
7	2/12 (1 right foot, 1 right hand)	3	0 *



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Figure 1 (a): Experiment paradigm of RUN1 and RUN2. RUN1 comprised a 5 minute rest period followed by 10 minutes of short motor movement task (twenty-four 3-second motor task trials performed separated by a random inter-stimulus interval (ISI) of 18-24 seconds). 3 movements were done in each short task trial, with four trial repetitions of each movement type except for the swallowing movement which was performed once. RUN2 comprised a 1 minute green fixation cross, followed by a 4 minute long motor movement task (six 10-second motor task trials with random ISI of 28-32 seconds), and then a further 1 minute of fixation cross. 10 movements were done in each long task trial, except for swallowing movement which were performed twice, with one trial repetition of each movement type. (b): Flow chart of decoding method. SPFM was performed on pre-processed data from RUN1 and RUN2. Six meta-maps were generated for each movement type using cluster-level inference in GingerALE. A decoding z-score, Z_m was then computed for each meta-map m at each time point to quantify spatial overlap between SPFM activation time frames and the m th meta-map. All decoding scores were FDR-corrected ($q < 0.05$).

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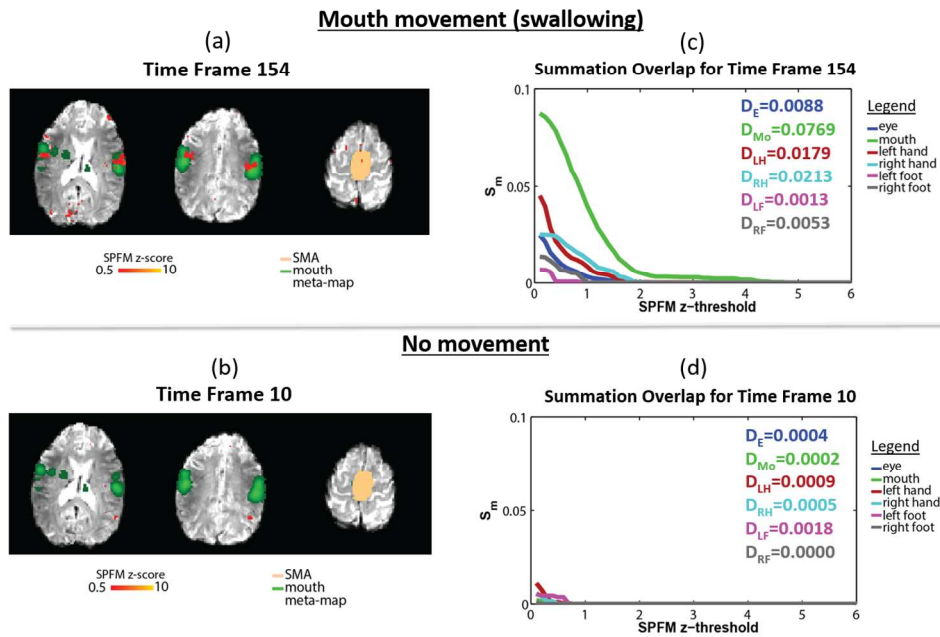


Figure 2: (a) Example SPFM maps for Subject 1 produced at time frame 154 of the short task RUN1 during a swallowing condition of the movement task detected by EMG. (b) SPFM map produced at time frame 10 of the short task RUN1 (no movement expected or detected by EMG). (c) Summation Overlap for all movement types for time frame 154. (d) Summation Overlap for all movement types for time frame 10. The decoding score, D_m , which is the area under each curves for (c) and (d), is given in respective colors indicated in the legend.

253x176mm (150 x 150 DPI)

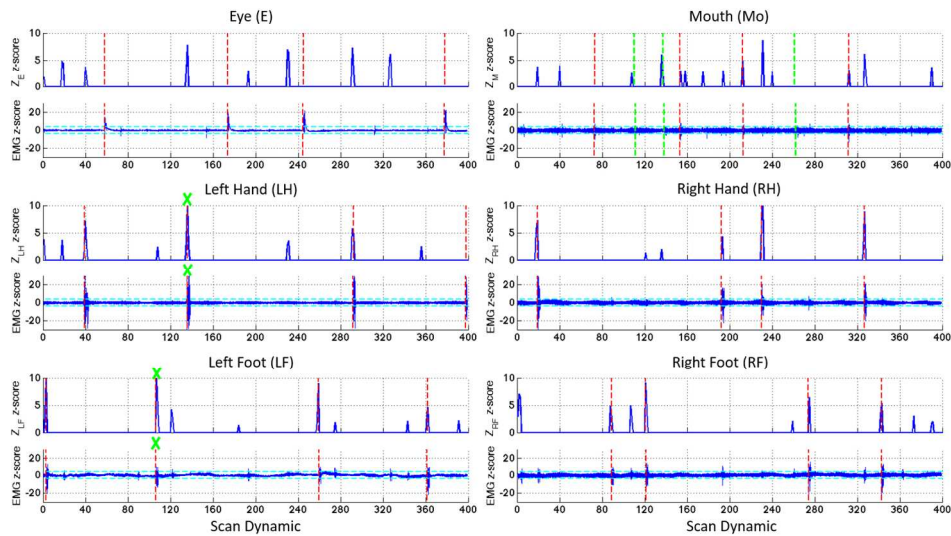


Figure 3: Decoding z-score Z_m (top row) and EMG z-score trace (bottom row) during short task paradigm in Subject 1 for each movement type: eye (E), swallowing (Mo), left hand (LH), right hand (RH), left foot (LF) and right foot (RF). Vertical dotted red lines indicate the times of the visual-cue stimulus, and vertical dotted green lines indicate movement detected by EMG trace. Horizontal aqua lines in EMG traces indicate $|z| > 4$.

Spikes in mouth EMG traces are not as apparent compared to other EMG traces because swallowing movements are reflected as distinctive waveform patterns, rather than an amplitude of the signal. Two non-task-based swallowing movement were detected by the decoding z-score at scan dynamic 110 and 137 (indicated by green cross), however ZLF and ZLH at these time points had higher magnitude than ZMo.

263x156mm (150 x 150 DPI)

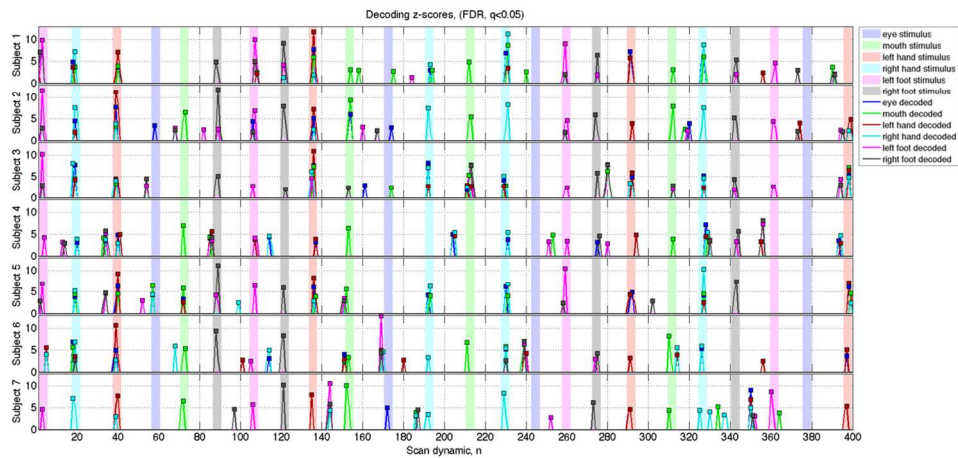


Figure 4: Decoding z-scores (FDR corrected, $q=0.05$) during short task for all subjects. The colored bands indicate the tasked stimulus given to the subject. The colored lines show the decoding z-scores for each meta-map type. The movement type with the highest decoding z-score is indicated by a colored square. The decoded movement types generally corresponded to the correct task (matching colored bands and squares), except for eye movements.

244x116mm (150 x 150 DPI)

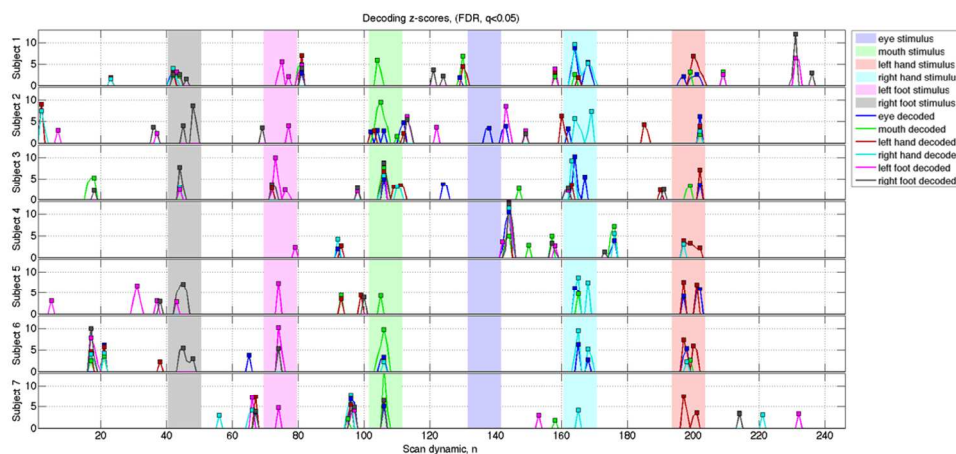
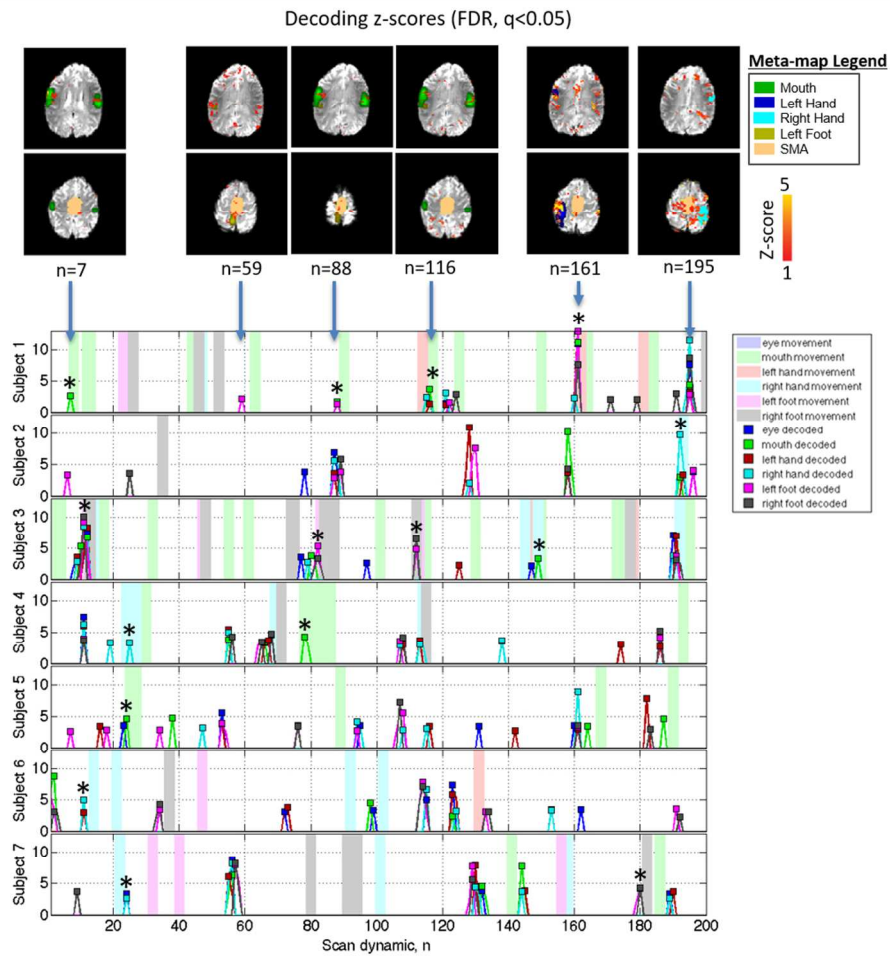


Figure 5 : Decoding z-score (FDR-corrected, $q=0.05$) during long task RUN2 for all subjects and movement types. The colored bands correspond to the periods of the tasked stimuli and the lines indicate the decoding scores. The colors corresponding to movement types displayed in the legend. Peaks of the decoding z-score are denoted with squares in respective colors. The movement type with the highest decoding score generally corresponded to visual-cued movement condition (matching colored bands and squares), except for eye movements.

215x113mm (150 x 150 DPI)



Decoding z-score (FDR-corrected, $q = 0.05$) for all movement types during 5 minutes resting state for Subject 1 to 7. Spatial maps showing SPM activations in z-score (red-yellow) overlay on meta-maps for time frames for $n = 7, 59, 88, 116,$ and 195 for Subject 1 are also shown at the top of the figure. The colored bands indicate movement detected in EMG traces with the movement type shown by the color in the legend. The colored lines show the decoding z-scores for each meta-map type. The movement type with the highest decoding z-score is indicated by a colored square. Asterisk (*) denotes decoded events that coincided with movements detected on EMG traces.

191x185mm (150 x 150 DPI)