NeuroImage 215 (2020) 116818

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

Transient spectral events in resting state MEG predict individual task responses

R. Becker [a,*], D. Vidaurre [a], A.J. Quinn [a], R.G. Abeysuriya [a], O. Parker Jones [b], S. Jbabdi [b], M.W. Woolrich [a]

[a] Oxford Center for Human Brain Activity, OHBA, Wellcome Centre for Integrative Neuroimaging, University of Oxford, UK

[b] FMRIB, Wellcome Centre for Integrative Neuroimaging, Nuffield Department of Clinical Neurosciences, University of Oxford, UK

ARTICLE INFO

Keywords:
Resting state
Bursts
Transient events
Brain oscillations
Individual variability
Hidden-markov-modelling

ABSTRACT

Even in response to simple tasks such as hand movement, human brain activity shows remarkable inter-subject variability. Recently, it has been shown that individual spatial variability in fMRI task responses can be predicted from measurements collected at rest; suggesting that the spatial variability is a stable feature, inherent to the individual's brain. However, it is not clear if this is also true for individual variability in the spatio-spectral content of oscillatory brain activity. Here, we show using MEG (N = 89) that we can predict the spatial and spectral content of an individual's task response using features estimated from the individual's resting MEG data. This works by learning when transient spectral 'bursts' or events in the resting state tend to reoccur in the task responses. We applied our method to motor, working memory and language comprehension tasks. All task conditions were predicted significantly above chance. Finally, we found a systematic relationship between genetic similarity (e.g. unrelated subjects vs. twins) and predictability. Our approach can predict individual differences in brain activity and suggests a link between transient spectral events in task and rest that can be captured at the level of individuals.

1. Introduction

Human non-invasive neuroimaging data is characterized by high inter-subject variability. Even for simple tasks such as moving a hand or seeing a well-defined visual pattern, the specific responses elicited in different subjects can be heterogeneous in terms of spatial location or extent, as well as magnitude, timing and oscillatory content. The origin of this variability is not clear, but there is increasing evidence that it reflects intrinsic, inter-individual differences in resting-state activity. Support for this hypothesis has been demonstrated recently using human functional magnetic resonance imaging (fMRI) data, where it was shown that task responses can be predicted from rest (Tavor et al., 2016). Specifically, spatial activation maps for a number of different tasks (motor, sensory, working memory) were reliably predicted from connectivity profiles derived from resting state data.

However, fMRI represents a rather indirect measure of brain activity. By contrast, magnetoencephalography (MEG) or electroencephalography (EEG) can capture the oscillatory and synchronized activity of neuronal populations and - unlike fMRI - can resolve brain activity at a temporal resolution down to milliseconds, reaching the temporal scale at which important aspects of cognition, and the neural dynamics that are tied to these processes, arise. Thus, the question arises as to whether features of M/EEG task responses can be predicted from resting M/EEG.

There is already a large body of work focusing on the link between rest and task processing in M/EEG. Features of the most prominent rhythms, such as alpha or beta oscillations, in human resting state M/EEG data are known to be functionally relevant and have considerable cross-subject variability (Klimesch, 1999). As in fMRI, the M/EEG literature has already demonstrated both the variability of transient electrophysiological features at rest, during task-processing and their functional relevance. For example, resting state features in EEG have been shown to impact on task responses (Becker et al., 2008; Mazaheri and Jensen, 2008; Nikulin et al., 2007), relate to perceptual and cognitive performance (Busch et al., 2009; Mathewson et al., 2009). On the other hand, ongoing activity in the alpha or beta frequency range is also highly variable during task processing and shows functional relevance during working memory tasks (Klimesch, 1997), observation of movements (Pineda et al., 2005) as well during effortful speech comprehension

* Corresponding author.
E-mail address: email@robertbecker.info (R. Becker).

https://doi.org/10.1016/j.neuroimage.2020.116818
Received 8 August 2019; Received in revised form 27 January 2020; Accepted 26 March 2020
Available online 7 April 2020

(Becker et al., 2013; Obleser and Weisz, 2012). The link between ongoing and task activity has been demonstrated both intra-individually (i.e. on a trial-by-trial level) and inter-individually (i.e. on a subject-by-subject level), and such links seems to exist beyond specific sensory and cognitive domains and have also been demonstrated invasively in animal brain activity (e.g. Arieli et al., 1996). While all these studies provide evidence of a link between rest and task activity in neuronal activity, a more direct link – i.e. predicting individual task responses from individual resting-state neuronal activity - is still missing for M/EEG.

In this study, we aimed to predict cross-subject variability of task MEG time-frequency responses using spatio-spectral dynamics as derived from resting MEG data. Recently it has been shown that task responses in M/EEG can be well represented using transient spectral events 'bursting' at fast time scales (van Ede et al., 2018; Shin et al., 2017; Vidaurre et al., 2016; Zich et al., 2018). We therefore hypothesised that subject-specific transient spectral events in resting-state neural activity might be predictive of subject-specific trial-averaged task responses, in a wide range of experimental conditions. To identify the characteristics of the transient spectral events, we used the approach of Hidden-Markov-Modeling (HMM). Hidden-Markov-Modeling is able to identify "states" in noisy neuroimaging data that get systematically revisited over time. HMMs with autoregressive observational models have previously been shown to be able to extract states that have distinct spectral content, in both rest and task MEG data (Vidaurre et al., 2016, Vidaurre et al., 2018b, 2018a; Zich et al., 2018; Quinn et al., 2018). Visits to the different states can be thought of as transient events with distinct spectral profiles. The time courses of these spectral events, or states, provides a high temporal resolution description of the dynamics of oscillatory activity; e.g. ongoing alpha and beta rhythms, or, in the case of task data, event-related components such as evoked or induced task responses.

Using HMMs with a focus on spectral patterns we sought to predict between-subject variability in the time-frequency responses in a parcellated whole-brain MEG data set involving a number of different tasks using resting state data, i.e. the aim is prediction in spatial, spectral and temporal dimensions. For this we use data from the Human Connectome Project (HCP), a consortium of several research institutes that has collected data of a relatively large number of MEG subjects and incorporates both resting state data and a range of task data, including motor movements, and cognitive tasks involving working-memory and language comprehension (Van Essen et al., 2013).

2. Methods

2.1. Subjects and data

The data used here are the resting state and task magnetoencephalography (MEG) data publicly available from the Human Connectome Project (HCP) consortium (Van Essen et al., 2013; Larson-Prior et al., 2013), acquired on a Magnes 3600 MEG (4D NeuroImaging, San Diego, USA) with 248 magnetometers. The resting state data consist of 89 subjects (mean 28.7 years, range 22–35, 41 f/48 m, acquired in 3 subsequent sessions, lasting 6 min each). Task data were available for a subset of these subjects, with 2 sessions per task. The tasks acquired in the MEG include a motor task condition - where hands or feet had to be moved paced by an external cue (every 1.2s), a working memory (WM) task - where people had to remember the occurrence a of n-back previously shown item (with $n = 0$ and 2) with the items being either tools or faces and finally, a third task group - involving language comprehension - where in one condition, subjects had to listen to a number of sentences (making up a complete story) and then answer questions regarding that story, and in another condition subjects had to solve math problems (Larson-Prior et al., 2013). Data were segmented to the onset of EMG (motor task), the non-target item (WM task), or to the onset of a sentence (language task). For each of the task groups, overlapping but not identical subsets of the total pool of resting state subjects was available (motor task $n = 56$, WM task $n = 70$, language comprehension $n = 72$).

We analysed 10 different task conditions in total across these 3 main task groups – 4 for the motor task (right hand, left hand, right foot, left foot), 4 for the WM task (0-back face items, 0-back tool items, 2-back face items, 2-back tool items, all being part of the non-target condition which also required a motor response), and 2 task conditions within the language condition - sentences vs. math problems.

2.2. Preprocessing

2.2.1. Source estimation and parcellation

For each subject, the MEG data were acquired in a single continuous run comprising both rest and task. We used the MEG data from the HCP database denominated as 'preprocessed' as starting point (i.e. with removal of artefactual independent components, bad samples and channels already performed, see Larson-Prior et al., 2013). Then, data were subject to bandpass filtering (1–48Hz, Butterworth) and LCMV beamforming (using beamforming routines from the Matlab based Fieldtrip toolbox (Oostenveld et al., 2011) and the in-house OHBA Software Library (OSL), (Woolrich, M. et al., 2011), resulting in 5798 virtual source voxels (with 8 mm grid resolution) and down-sampled to 200 Hz. In order to reduce dimensionality of the analysed data, we used a custom parcellation of 76 parcels covering the whole brain, extracting the first principal component (PC) across all time-courses within each parcel. The parcellation was created in such a way that each first PC explained about 60% of the variance across all voxels within each parcel by starting with 2 large parcels covering each hemisphere and then subsequently splitting these parcels into smaller ones). The parcellation was based – analogous to all other preprocessing steps – on the resting state data only.

Note that all resting state runs for a subject were acquired in a single session. As a result, we concatenated the resting state runs for a subject, and applied a single beamformer, parcel time-course extraction and spatial leakage reduction. Then, the transformations (learnt only from the rest data for a subject) are applied to the task data runs for any subjects we are looking to predict. This ensures maximum consistency of within-subject pre-processing for all sessions, without having knowledge of, or being biased by, any task data information from the same subject.

To reduce spatial leakage, we used the multi-variate orthogonalisation approach on the parcel time-courses, as described in (Colclough et al., 2015), using the 'closest' implementation.

2.2.2. Task data epoching

For the motor task, data were time-locked to the onset of the electromyogram (EMG), for the WM task, epochs were locked to the visual onset of the (non-target) item and for the language comprehension task the beginning of the sentence or maths problem was the time-locking event. To ensure consistency of the concatenated data sets, both resting state data and task data were normalized to zero mean and unit variance (performed per subject and parcel). Motor task epochs were segmented from −1.1 to 1.1secs, working memory task data and language task data from −1.1 to 2.2 s. Baseline correction was performed from −0.5 to −0.2s.

2.3. Conventional estimate of time-frequency task responses

We performed conventional wavelet (WL) time-frequency analysis (7 cycles, Morlet mother wavelet) for the segmented task data, serving as a comparison with the HMM-based (regularised) task responses at the group level (described later). The WL based task responses were baseline corrected in a pre-stimulus time window (−0.5s to −0.2s for all task conditions). If not specified otherwise, general custom Matlab scripts were used (Matlab R2016b, Natick, USA) and the in-house OHBA Software Library (OSL), which is built on Fieldtrip and SPM, available at https://github.com/OHBA-analysis/osl-core).

2.4. Prediction of subject-specific time-frequency task responses using resting data

In order to predict task responses - in space, time and frequency - from resting state features, we hypothesised that subject-specific transient spectral events, or bursts, found in resting-state neural activity might be predictive of subject-specific trial-averaged task responses. To identify spectral events we used the approach of Hidden-Markov-Modeling (HMM), which has previously been shown to be able to identify spectral events independently in task and rest MEG data (Baker et al., 2014; Quinn et al., 2018; Vidaurre et al., 2018b, 2016).

Specifically, we used the HMM with an Auto-Regressive observation model (HMM-AR) to learn the subject-specific spectral content of these transient events in resting MEG data. This was then combined with a group averaged description of when these transient events tend to re-occur in the task response, to produce subject-specific predictions of the task response. We carried out this approach one parcel at a time, using the pipeline outlined in Fig. 1., summarised by the following steps:

1) **Training**:
   a. We used the HMM to identify transient spectral events in the rest data (done separately for each parcel, all parcel time-series concatenated over subjects). Note that each HMM state corresponds to a spectral event of a certain type. These resting-MEG HMM states, or transient spectral event types, are characterised by both when they occur (i.e. the state time courses) and their group-averaged or subject-specific spectra. We refer to these spectra as ***RHS spectra*** (which is short-hand for Resting-MEG-derived HMM State (RHS) spectra). Subject-specific, individual RHS spectra are obtained by spectral analysis of the RHS time-courses in the subject-partitioned resting data.
   b. We then estimate the state time courses of when those resting-MEG states, or transient spectral event types, tend to re-occur in the task data. The resulting time courses were then averaged over trials to compute an evoked response for each state. We refer to these as ***RHS task responses.***
2) **Prediction:** Finally, we predicted the task response of a left-out (LO) subject. We did this by combining the subject-specific RHS spectra for the LO subject (this only uses the rest data for that subject) with the group-averaged RHS task responses (where we have excluded the RHS task response for the LO subject).

This pipeline is specified in more detail in Supplementary Fig. 1 and in Supplementary Methods (section 1., "***HMM framework: training, spectral estimation, extraction and prediction of task responses***").

2.5. Validation of prediction

In the validation step, we assessed the quality of the predictions by comparing the LO subject's time-frequency predicted task response (PTR) (from Supplementary Fig. 1F) to their actual task response (ATR). The HMM-AR limits the dimensionality of the PTR (because the autoregressive observation model used by the HMM has only 5 parameters, and because there are only 4 HMM states) so it is by design a regularised estimate of the ATR. To ensure that we are comparing like-with-like, we applied this regularisation to both the PTR and ATR, i.e. we stay within the HMM framework to estimate both the *PTRs* and *ATRs*.

To assess the quality of the prediction, linear correlation analysis was used to compare the predicted (*PTRs*) and actual task response (*ATRs*) of all subjects. Baseline-corrected *PTRs* (i.e. 2D time-frequency maps), that is, the full time-frequency task response matrices [with the available peri-stimulus time ranges of −1.1 to 1.1s for the motor task, −1.1 to 2.2s for the working memory and language task and the full frequency range of 1–48 Hz] were vectorized and concatenated over all parcels for each subject. That is, all information pertaining to the task responses enters this validation analysis in the shape of one long vector per subject (and task). The reason for using baseline corrected task responses (instead of looking at absolute power changes) is that this represents a stricter and more conservative test of prediction. Without baseline-correction, the spectral average state (i.e. the task spectrum) enters the correlation and distorts, that is, it overestimates results, while attenuating the sensitivity to how well task dynamics are captured. Then these concatenated *PTRs* were correlated with the *ATRs* of all subjects (including its own *ATR*). In

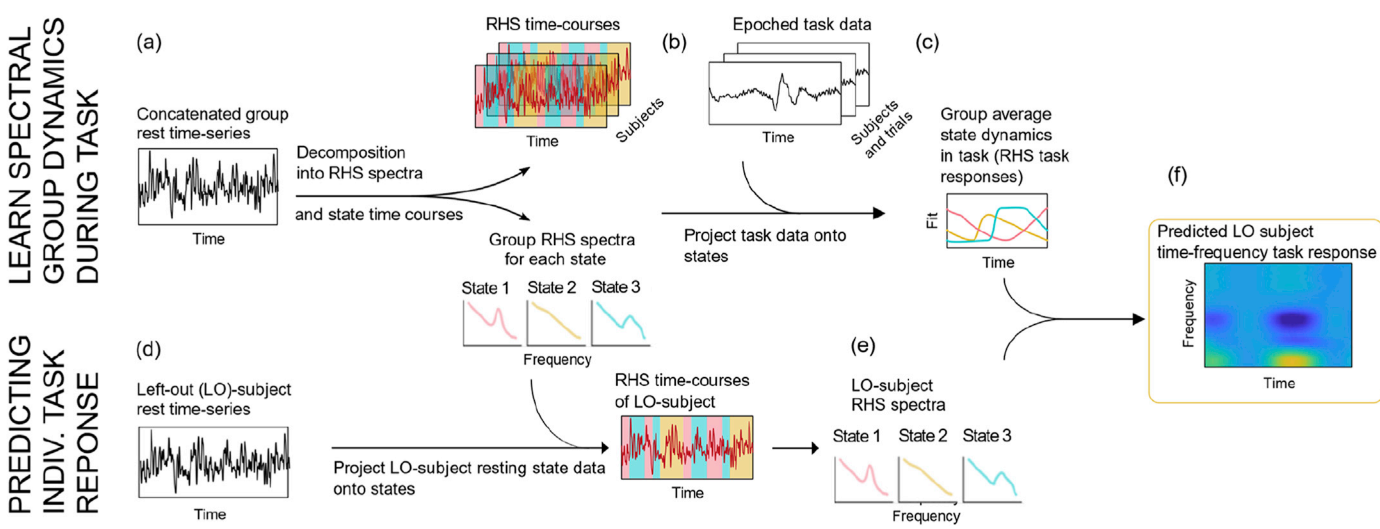

Fig. 1. An overview of the approach, shown for one task condition and one parcel. **a-c. Training stage. (a)** By using Hidden-Markov-Modelling (HMM), Resting-MEG-derived HMM states (RHS) are identified on the entire group concatenated resting state time-series, resulting in the group-averaged RHS spectra. Note that each HMM state corresponds to a spectral event or burst of a certain type. **(b)**. The epoched task data for all subjects and trials is projected onto the group-averaged RHS spectra, to identify when the RHS tend to reoccur in the task response, resulting in group-averaged RHS task responses. **(c). d-f. Prediction of the task-response** for the left-out (LO) subject. **(d)** The LO subject's resting state activity is projected onto the group RHS spectra to identify when the group RHS tend to occur in the LO subject's rest data, yielding LO-subject RHS time courses and based on the subject-specific state-time courses, the refined, individual RHS spectra specific to the LO-subject **(e)**. Finally, the group-averaged RHS task responses, from panel **(c)**, and the LO subject-specific, i.e. individual, RHS spectra, from panel (e), are combined to create a LO subject-specific prediction of the time-frequency task response **(f)**. This is a summary of our approach; a more detailed schematic, specific to the use of HMM-AR in this study is depicted and described in Supplementary Fig. 1.

case of a good prediction, the individual predicted task response should be more similar to the actual task response of the same subject than to the actual task responses of any other subject. After performing this correlation, correlation coefficients were normalized (demeaned, with unit variance) over rows and columns, since we were not interested in the mean or different variances of actual vs predicted task responses in different rows and columns (analogue to Tavor et al., 2016). This normalization is performed to enhance sensitivity of estimating the *relative* predictability of one subject vs another rather than *absolute* predictability. As an illustration, one subject which shows a very typical average response will likely be predicted better on average than another. The normalization removes such absolute baseline differences, both in rows and columns and emphasizes how well a subject is predicted in relative terms. In order to determine the statistical significance of this effect, a two-sample *t*-test was performed, to test whether diagonal and off-diagonal samples come from the same distribution.

A detailed description of the approach for generating the actual task responses (ATR) within the HMM framework and the visualisation and comparison to conventional task responses can be found in the Supplementary Material (Supplementary Methods section 2., "***Characterisation of identified HMM states: spectral features and their modulation in task conditions***" and Supplementary Fig. 2).

2.6. Sources of variability of prediction performance across tasks and subjects

Next, we examined whether there is any systematic variation in how well we can predict different tasks and different subjects. Specifically, we investigated the relationship between prediction performance and a measure of the 'stability' of each subject's first-level task. Prediction performance was quantified using the average diagonal value of the correlation matrix (see Fig. 4 later), and the task stability was quantified (within subjects) using the resulting t-value over all trials for a time window of interest from 0.1s to 0.5s post-stimulus, frequency range from 8 to 26 Hz (testing the difference from zero), and for a representative parcel-of-interest for each task, as shown in Fig. 3. For the motor task, we chose a parcel corresponding to the contra-lateral motor area, for the working memory task we chose a parcel in proximity to visual cortex, and for the language task we chose a parcel near the auditory cortex. These measures were computed for every task and subject.

2.7. Influence of genetic factors on prediction of task responses

The MEG HCP data contains a roughly equal mix of monozygotic (MZ), dizygotic (DZ) and unrelated (UNREL) subjects. It has been previously shown that the functional connectomes of more related siblings are more similar in MEG and fMRI (Colclough et al., 2017; Vidaurre et al., 2018b, 2018a). Here, we wanted to examine whether there is also any systematic structure in cross-subject predictions, i.e. whether the ability to predict one subject's task response from another subject's resting state features is governed by genetic similarity (for example from one twin to another etc.). To do so, after grouping the subjects into groups MZ, DZ and UNREL, for all tasks at hand ($n = 10$) we accumulated the previously computed and normalized correlation coefficients for predicted vs. actual task responses for each pool of subjects (see "Validation of prediction approach" for the normalization approach).

In order to test whether the difference between cross-subject predictability is systematic, we performed permutation tests for the following groups: MZ vs DZ, DZ vs UNREL, with another reference group, SAME, testing for how well we could predict from the actual subject (see "Validation of prediction approach"). For each grouping, labels of the two conditions were shuffled 1000 times and we compared the actual group mean difference against the distribution of differences from the permutation distribution.

3. Results

3.1. Between-subject variability in task and rest

We start by illustrating the nature of subject variability apparent in task and rest data, and the potential relationship between them. This is shown in Fig. 2, for the example of the right-hand movement task, locked to the EMG onset. Fig. 2A shows the group-averaged resting state spectra; and Fig. 2D shows a prominent, typical task-induced beta event-related desynchronisation (ERD). Next, we looked to see if there were any indications of subject-specific relationships between the spectral properties of the trial-averaged task beta ERD and the spectra in the resting state data.

First, we looked at the **amplitude** of the beta ERD, by plotting in the second column of Fig. 2 the power spectra in rest and task (calculated during the ERD) over subjects, with the subjects ordered by their task beta ERD amplitude. Second, we looked at the **peak-frequency** of the beta ERD, by plotting in the third column of Fig. 2 the same power spectra in rest and task over subjects, but now with the subjects ordered by their task beta ERD peak-frequency.

This illustrates two points. First, the subject-specific trial-averaged task and rest spectra show a considerable amount of between-subject variability, in terms of both the amplitude and shape of the spectral profiles. Second, there appears to be a qualitative relationship between the task and rest spectral profiles of individual subjects. Most notably, the task beta ERD **peak-frequency** ordering reveals a similar trend over the subjects between task (Fig. 2F) and rest (Fig. 2C). For example, subjects that have a high task beta ERD peak-frequency, also tend to have a higher amount of power in high beta than low beta in the rest data. It is these types of relationships that our approach leverages to allow the prediction of trial-averaged task spectral responses from rest data.

3.2. Data: group level task responses

Before proceeding to subject-specific task-response prediction, we examined the distinct group-averaged task responses for the different tasks that we will be predicting. The group-averaged conventional wavelet (WL) based task responses for the three main conditions in these tasks – a motor task, visual working memory and a language comprehension task - are shown in Fig. 3.

The motor task (Fig. 3A) shows the typical movement-related alpha and beta ERD in a contralateral motor-cortex associated parcel (approximate parcel location is indicated by red dots on the rendered brains) and a typical motor-evoked response, i.e. a power increase in the lower frequency range (especially in the contralateral motor areas). The group task response for the visual working memory task (Fig. 3B) shows both the typical visual alpha ERD following a visual stimulus (which occurs during this task) and the motor preparation component reflected by ERD in the beta band contralateral to the required button press (needed to respond to matches/non-matches). Both the motor component as well as the visual component show power increases in the lower frequency range reflecting the evoked responses usually associated with such a task. The language comprehension task (Fig. 3C) shows alpha ERD in a parcel encompassing auditory cortex and higher auditory areas, as well as typical language-related theta power increase. Both are sustained for the duration of the sentence presentation (exceeding beyond the shown time window).

These average task responses illustrate that while the tasks share some common spectral features, such as alpha or beta ERD, they vary in their exact spectral profile, temporal dynamics and spatial patterns.

Before any prediction can take place, one important question is whether the HMM-AR is a viable choice for extracting critical features from rest that might constitute the task response features that we want to predict. To get a qualitative answer to that question, we used the HMM-AR on the task data, however with the observation model held fixed. This basically corresponds to describing the task data using spectral events

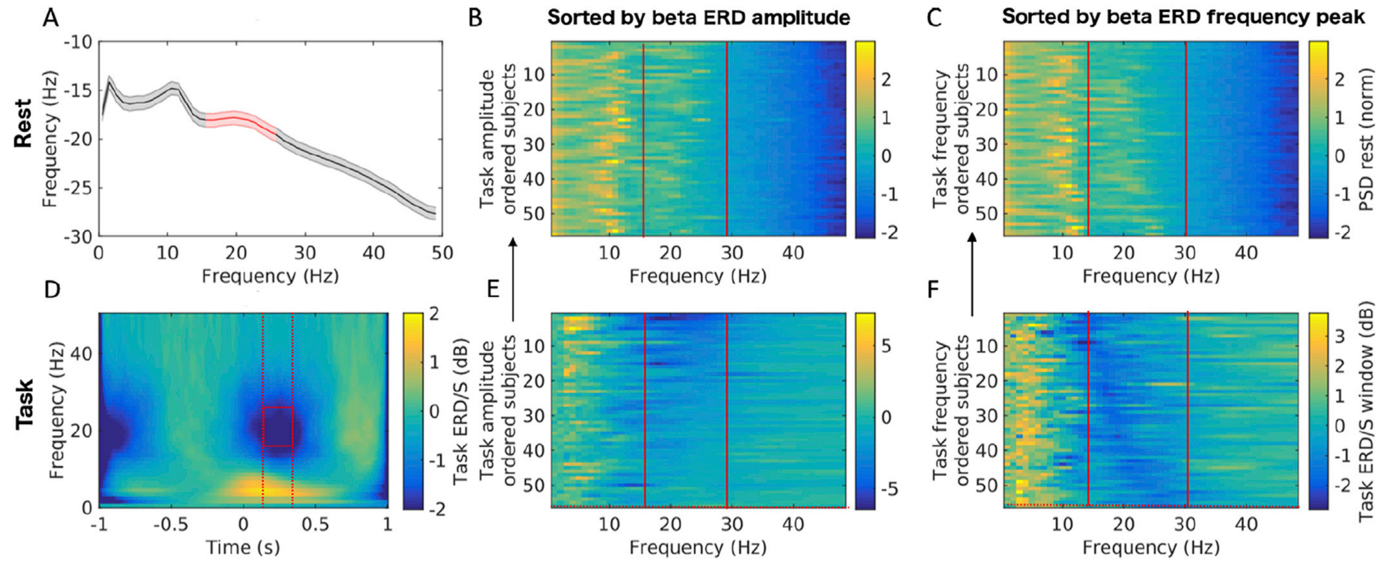

Fig. 2. Illustration of the subject variability in task and rest spectral content, and the potential relationships between them. As an example, we use the right-hand movement task, locked to EMG onset, and resting state data from the same motor-area parcel. **A.** Group-averaged power spectrum of resting data from a parcel in the left motor cortex (data was high-pass filtered above 1Hz). **B, C.** Resting state spectra (frequency on x-axis) of individual subjects (on y-axis) ordered by task features in E and F (i.e. beta amplitude and beta frequency). **D.** Time-frequency amplitude response in the task condition, showing a beta-band event-related desynchronisation (ERD) (red square), red-lined window is used for sorting in E and F. **E.** Task power spectra during the ERD for each subject, ordered by their beta ERD amplitude (extracted from the average over the red time-frequency window in D). Note that the task power spectra in E and F were computed by averaging over the ERD time-period, i.e. within the time-window indicated by the dashed red-lines in D. This ordering index was used in B. **F.** Same power spectra as E, but now with subjects ordered by their beta ERD peak-frequency (found within the time-window indicated by the dashed red-lines in D) - this subject ordering index is used for the resting state data in C.

that had been identified at rest only. The results can be seen in Supplementary Fig. 2, for all groups of task responses we examined – motor, working memory and language task responses. In general, the features extracted at rest are able to describe the main features in the group-average task data, task-related increases in power usually reflecting evoked responses as well as task-related decrease in mostly alpha or beta power reflecting typical event-related desynchronizations (ERD).

3.3. Prediction of subject-specific task responses

We next examined if we could predict the spatial and spectral content of an individual's task response using features estimated from the individual's resting state data. Specifically, we hypothesised that transient spectral 'bursts' or events in the resting state would predict transient spectral events in the task responses.

To do the subject-specific task-response prediction we applied the pipeline outlined in Fig. 1, where we obtained the predicted task responses for all task conditions, parcels and subjects. In Fig. 4, the validation results for each of the 3 main types of tasks (motor, WM, language) are shown (illustrated for the same tasks as in Fig. 3 and Supplementary Fig. 2). Fig. 4A shows the correlation matrix that reflects how strongly the actual task responses correlate with the predictions, either from the same subject (indicated by values in the diagonal) or from other subjects (indicated by values in the off-diagonal part of the matrix). A good prediction should result in the diagonal (prediction of same subjects) prominently standing out. Fig. 4A shows the 'raw' correlation coefficients for this validation step, while Fig. 4B shows the same correlation matrix after normalization (of row and columns, respectively). In order to statistically test the difference between same-subject prediction vs random-subject prediction, we tested the null hypothesis that both these groups (same vs other, i.e. in-vs off-diagonal) come from the same distribution (using a two-sample Student's t-test). This was rejected for all task conditions, as all p-values were less than 1.86×10^{-5} (for the math problem solving task). Thus, predictions for all tasks are better when using resting state data (specifically their spectral profiles of the different types of spectral events, or states, as identified by HMM-AR in rest data) from the same subjects as compared to random subjects (defining our 'chance level' in the present case).

We next sought to characterise the nature of the between-subject variability that we are able to predict with our approach. Supplementary Fig. 3 shows three example subjects, illustrating the between-subject variability that is being predicted in two ways in the right-hand motor task. First, we show the average predicted power in a post-stimulus time-window (190–390 ms) in the beta band. Second, we show the predicted task-related *time-frequency (or spectro-temporal) variability* in a motor parcel contralateral to movement. In summary, this illustrates how the predictions are reflecting both spectro-temporal and spatial aspects of between-subject task variability.

3.4. Prediction quality across tasks

Another question that is important to address is the variability of prediction performance, i.e. how well we predict subject specific task responses from rest, in the tasks examined and what is the source of it. While all task conditions yield predictions that are significantly better than chance, the quality of the predictions varies to some extent. We hypothesised that one potential source underlying the variability in prediction quality might be the (cross-subject) task-specific variability of signal-to-noise ratios (SNR). The result is visualised in Supplementary Fig. 3. SNR of task responses was defined by the subject's first-level statistics (i.e. t-values indicating the within-subject level of significance of the observed task responses). For each task - both on a group averaged as well as on the individual subject level - stronger and more stable responses (as indicated by t-values, plotted on the x-axis) imply better prediction (i.e higher normalized correlation coefficients, on the y-axis). In general, the motor task conditions (right/left hand and feet) are predicted best, followed by the working memory conditions, and finally, the language comprehension task conditions (sentence comprehension, math

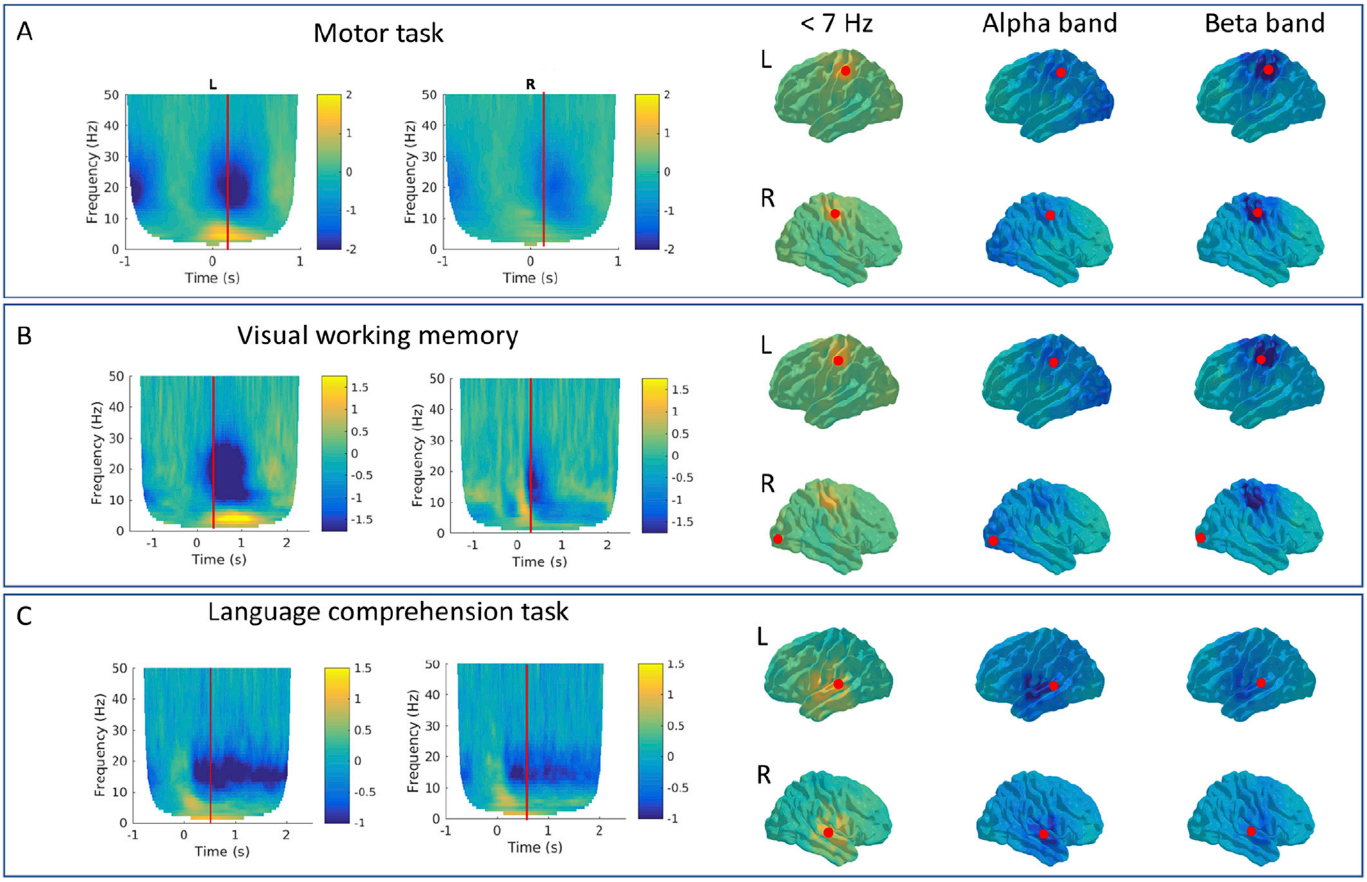

Fig. 3. Group-level summary of the different task responses used in this study. **A**. Motor task (a right-hand movement, time-locked to the movement onset). **B**. Visual working memory task (2-back, faces, time-locked to appearance of the non-target items). **C**. Language comprehension task (time-locked to beginning of a sentence). On the left of each panel, is the wavelet-based time-frequency maps locked to task onset (shown separately for the left and right hemisphere), for the parcels indicated by the red dots on the rendered brains on the right of each panel. The red line in the time-frequency plots indicates the time-point show in the rendered brains on the right side, which are shown for three different frequency ranges, corresponding to sub-alpha (<7 Hz, including theta and delta range), alpha, and beta.

problem solving). A similar analysis where we examined another potential source of prediction performance variability - effect size, i.e. subject-specific average amount of alpha or beta ERD rather than subject-specific SNR (as done above) - yields no such relationship (results not shown).

3.5. HMM predicted task responses show hereditary structure

We asked how the genetic structure, a feature available in the present HCP data set, is related to predictability (Fig. 5). We hypothesised that task responses might be better predicted from resting state data of genetically more closely related subjects (e.g. identical or non-identical twins) than from resting state of completely unrelated subjects.

Non-parametric analysis of variance revealed that the normalized correlation coefficients (i.e. the similarity between prediction and actual task responses, see Methods) pooled into groups; reflecting that same subjects (SAME), identical twins (MZ), non-identical twins (DZ) and the remainder (UNREL) are not originating from the same distribution (as determined by permutation testing). Non-parametric (rank-based) post-hoc testing between the groups showed that all differences in prediction performance between groups were significant ($p_{SAME\_vs\_MZ}$, $p_{MZ\_vs\_UNREL}$, $p_{DZ\_vs\_UNREL}$ all < 0.001, cf. Fig. 5). Generally, correlation coefficients are higher (i.e. predictions are better) the more genetically similar subjects are, in terms of the ability for the resting state data from one subject to be able to predict another subject's task response.

4. Discussion

4.1. Summary and interpretation of results

We have shown that subject-specific trial-averaged task responses can be predicted in task MEG using subject-specific transient spectral events, or bursts, identified in resting-state MEG data. We have shown that this prediction is made without prior knowledge of the task responses of specific subjects and is mediated by hereditary factors. This has been demonstrated using the HCP MEG data; a large, freely available data set with a set of diverse experimental conditions ranging from simple hand movements to more cognitively demanding tasks involving working memory, attention and language processing.

To identify transient spectral events, or bursts, we used the HMM. In this approach, each HMM state corresponds to a spectral event or burst of a certain type. The HMM has been previously used to identify transient events in both rest and task data in MEG (Baker et al., 2014; Quinn et al., 2018; Vidaurre et al., 2018b, 2016), fMRI (Vidaurre et al., 2017) and simultaneous EEG-fMRI (Hunyadi et al., 2019). Here we used a region-by-region HMM-AR to identify transient spectral events defined as having distinct spectral profiles, in order to link rest and task with the following findings.

First, the spectral properties of the different transient spectral events represented by the HMM states purely extracted from rest were shown to be relevant and effective in describing task dynamics at the group-averaged level. Subsequently, subject-specific spectral profiles of

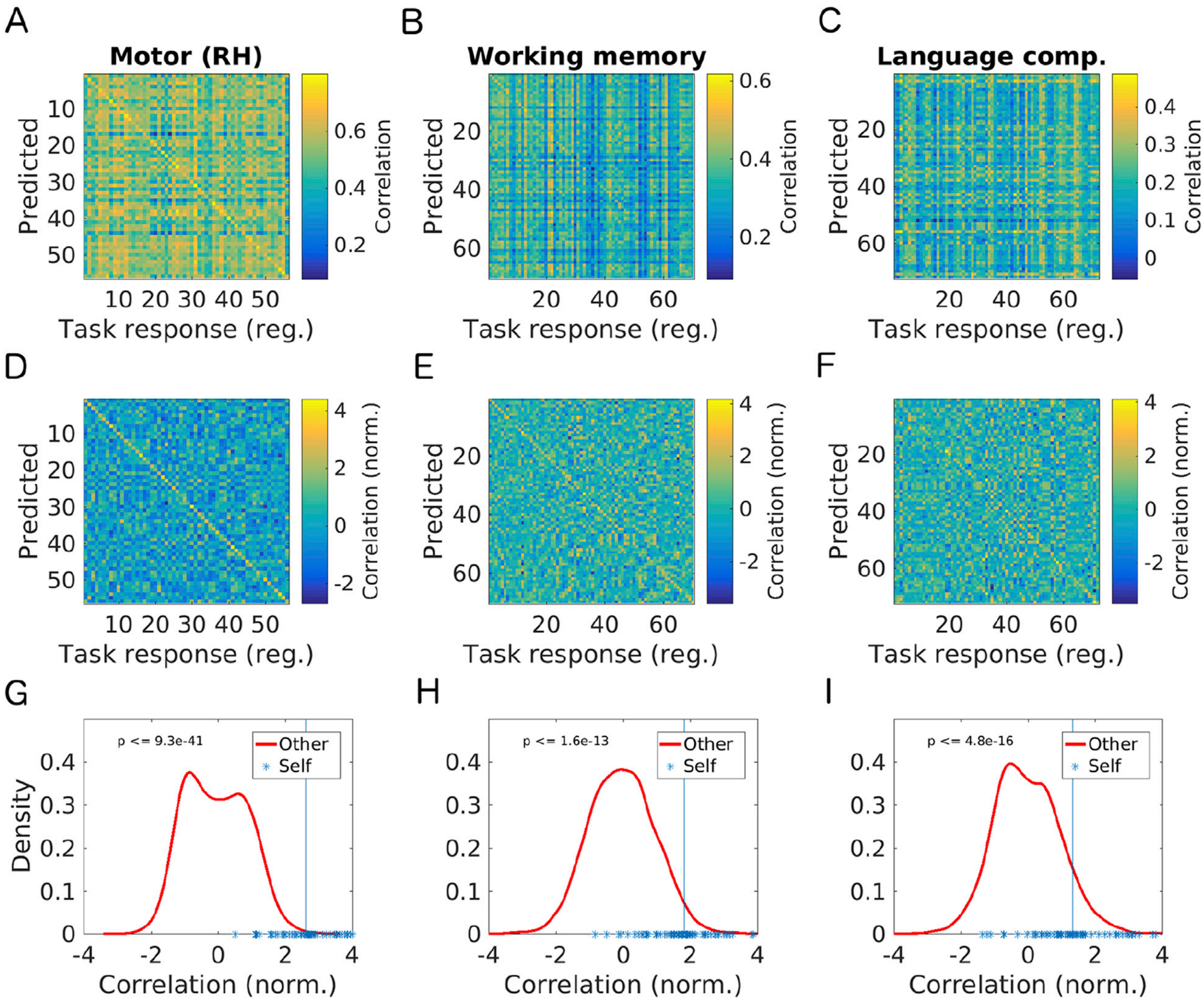

Fig. 4. Group level statistics for the prediction of subject-specific task responses (here one task condition is shown for each group of tasks – motor, working memory and language comprehension - showing the level of correspondence between actual task responses and their predictions. **A-C**. These matrices show the correlation coefficients between actual and predicted task responses of either the same subjects (in the diagonal) or of different subjects (in the off-diagonal). Results are shown for a motor task (right hand movement, A), working memory task (2-back, face stimuli, B) and language comprehension task (sentence understanding, C), respectively. **D-F**. Same task conditions, now with the correlation coefficients normalized over rows and columns (see Methods). **G-I**. Predicted task-responses and actual (HMM-regularised) task responses from the same subjects are more similar to each other than pairs of task response and predictions from different subjects (distribution is visualised by the red lined plot). The asterisks represent the values in the diagonal from D-F, the blue vertical line the mean and the red line distribution represents the distribution of the off-diagonal values from D-F. All task conditions were predicted above chance level.

transient spectral events identified by HMM-AR were then used to predict trial-averaged task dynamics on a single-subject level (Fig. 1, Supplementary Fig. 1). We found that the accuracy of the presented approach typically depends on two factors: The accuracy of the individual spectral profiles of the spectral events as extracted by HMM-AR, and the accuracy of the predicted state dynamics, i.e. the state time-courses or rate of occurrence of the spectral events represented by each state, for the states associated with these spectral profiles. Both these properties critically affect the prediction accuracy, since these two features ultimately generate the predicted ('HMM-regularised') time-frequency task responses in our model.

With respect to the different task conditions, we saw that task response predictions worked best in task conditions with strong and robust event-related task responses both at the subject and group level (Supplementary Fig. 4). This relationship is likely to come from two different sources. First, a robust task response means that during the training step in our framework, the actual task dynamics, i.e. the state time courses of the hidden states (which serve as a model for the left-out subject) are better estimated when task responses are robust (i.e. less noisy and more genuinely subject-specific); this is true for both subject and group level estimations. Second, a robust response also means that ERD behaviour is better estimated in terms of its precise spectral properties (i.e. its peak frequency).

4.2. Previous work and related approaches

The results in this work may be relevant for the incipient debate on the interpretation of frequency-specific patterns of neural activity. The success of using the HMM to identify transient spectral events in order to link rest and task implies that transient spectral events, or bursts, are a useful description of brain activity in electrophysiological data. It remains to be seen, but it is possible that a hybrid description of bursts and sustained rhythms could be even more powerful (Shin et al., 2017; van Ede et al., 2018). However, a complete comparative analysis with non-bursting representations of spectral activity is required to fully support this idea.

In a broader sense, the present study is part of a body of work that tries to link rest to task features, or, more generally, structure to function.

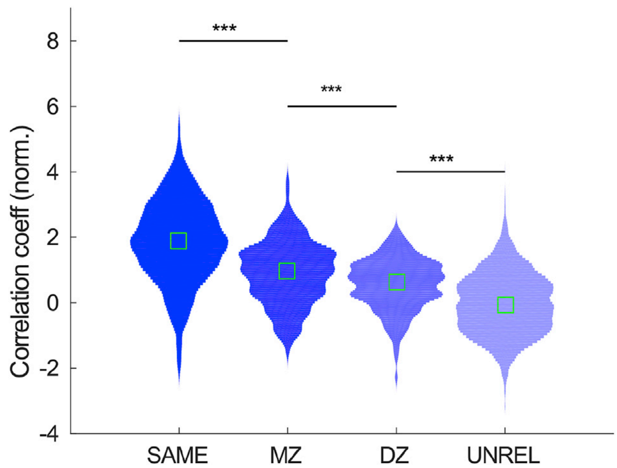

Fig. 5. Genetic factors play a role in cross-subject predictions, with subjects being better predicted by their genetically closer counterparts than by unrelated subjects. As expected, when pooling over all same-subjects ('SAME'), the normalized correlation coefficients are highest (corresponding to the distribution of all pooled diagonal entries from correlation matrices in Fig. 4). The second-best prediction across subjects is obtained when predicting task responses from one monozygotic twin's rest data to its sibling (labeled 'MZ', sharing 100% of their genetic information). For dizygotic twins (labeled 'DZ', 50% of shared genetic information) predictions are slightly worse (not significant compared to MZ), however they are still significantly better than when predicting task responses of random subjects ('UNREL', i.e. unrelated subjects with no shared genetic information). Stars indicate level of significance (***$p < 0.005$, results of permutation testing (with 1000 permutations), following Bonferroni correction for multiple comparisons), light green boxes indicate the median.

Previous approaches have shown links between resting state connectivity patterns and task activations (Biswal, Yetkin, Haughton and Hyde, 1995; Cole et al., 2016; Tavor et al., 2016), connectivity and subjects or behavioral measures (Shen et al., 2017a,b; Smith et al., 2015), anatomically related structural features such as grey matter volume linked to behavioral skills such as navigation (Maguire et al., 2000) as well as links between structure and spatio-spectral content (Abeysuriya et al., 2018; Hadida, Sotiropoulos, Abeysuriya, Woolrich and Jbabdi, 2018). All of these findings point to the functional relevance of inter-subject variance – variance that is necessarily eliminated by conventional approaches such as averaging (Seghier and Price, 2018). This approach builds upon the previous work to show the relevance of this variability in the time-frequency domain by both representing inter-subject variance and showing its link with the resting state.

The evidence that there is a hereditary component (Fig. 5) - meaning that prediction from resting state data of genetically related subjects yields better task predictions than predicting from unrelated subjects - adds weight to this finding. It supports the idea that these inter-subject differences are not trivial, but biologically meaningful, since related subjects show related MEG patterns. Previous reports already indicated that inter-subject variability, specifically of functional connectivity in resting state (Colclough et al., 2017) as well as spontaneous HMM state (and meta-state) dynamics (Vidaurre et al., 2018b, 2018a) have a strong genetic component, and the finding of genetic influence in the present results is another hint at the relevance of genetic factors for subject variability. Both the spectral profiles and the mapping from resting state to task state dynamics should have some hereditary component to them to yield the present results (being a combination of these two) - however, no systematic comparison has been done to assess their relative contribution more precisely. Regarding the origin of this genetic component – one possibility might be for example cortical folding, which is known to be hereditary to a certain degree – which could affect measurements on the scalp and ultimately source reconstructed rest and task signatures. However, while this might explain spatial variability it is less clear how this would explain spectral variability (such as differences in peak frequency for alpha or beta rhythms, for example).

With respect to predicting task activations from rest, what differentiates our approach from most of the previous approaches (Shen et al., 2017a,b; Tavor et al., 2016) is the challenge of an effectively 3-dimensional task-structure (time-frequency-space), instead of 1D spatial activation maps. Taking this into account, the results are quite encouraging and in terms of statistical robustness comparable to previously reported results for prediction of spatial activation maps in fMRI (Tavor et al., 2016). The data set used in the present study shares a subset of task conditions with the fMRI study (both data sets being part of the Human Connectome Project, Larson-Prior et al., 2013) and a subset of subjects. Interestingly there is one other noteworthy difference: While our approach (in MEG) seemed to be best at predicting 'simple' tasks (involving hand or feet movements), and less good at predicting more cognitive tasks, the approach in Tavor et al. (2016), for fMRI, showed an opposite effect, performing best in highly cognitive tasks (e.g. language processing). One reason for this might be the sensitivity of our model to spontaneous or induced oscillations such as alpha or beta rhythms, known to be modulated most clearly in functionally more 'fundamental' sensorimotor and posterior visual areas, and detected less in frontal or other more 'cognitive' areas higher up in the neural processing hierarchy (Srinivasan et al., 2006).

The presented framework, i.e. using transient spectral events identified via the HMM-AR to predict subject-specific task responses is not the only way to predict trial-averaged task responses in M/EEG, or related electrophysiological, data. Any approach that is capable of decomposing resting state activity into spatio-spectral modes might be similarly used to identify links between rest and task activity. For example, methods like non-negative matrix factorization (Lee et al., 2011), autoregressive modes (Porcaro et al., 2009) or other sliding window approaches (O'Neill et al., 2017) are possible options. However, the need for sliding windows - or entirely collapsing spectral features over time - differentiates these from the HMM approach. The unsupervised decomposition of a time-series into consistently reoccurring, transient spectral events with distinct spectral modes - without the need of fixing window length or imposing another temporal structure - is potentially beneficial for the identification of relevant, yet transient and dynamics patterns needed to predict task responses in M/EEG.

Regarding the existence of potentially more straight-forward approaches, similarly to the scenario illustrated in Fig. 2, one has to note that while simpler approaches in a limited use scenario might exist – i.e. for isolated frequency bands, parcels, or tasks – we here present a data-driven, unsupervised approach with no strong a-priori assumptions about the exact nature of the link between resting state and task data. Any approach that wants to offer a more general solution, is likely to follow the principle as outlined in Fig. 1, extracting features from rest and mapping these onto features in the task data in order to predict their variability across subjects.

4.3. Limitations and challenges

The approach presented here has its limitations. One potential limitation is that the version of the HMM-AR approach used here for estimating spectral events (which were then used for the prediction of subject-specific task-responses) – was a mass-univariate approach. Since it uses a different HMM-AR on the single time-course of data from each brain region. Thus, by necessity, it ignores any cross-regional interactions. The univariate approach might also be a factor that explains that in our model, sensorimotor task might be predicted better than more cognitive tasks, but this would need further investigation. For future studies, multivariate approaches based on time-delay embedding (Vidaurre et al., 2018) might be exploited to enable the incorporation of additional features (for example, connectivity measures) with the hope to potentially increase prediction quality.

Nonetheless, the mass-univariate approach pursued here has demonstrated success in predicting subject-specific properties in diverse MEG task responses. Utilizing similar HMM methodology to identify transient spectral events in task data, a recent study has shown changes in HMM state dynamics reflecting modulated beta oscillations as a function of motor learning (Zich et al., 2018), adding support to the usefulness and sensitivity of using the HMM with activity from one brain region at a time.

4.4. Outlook & conclusion

Being able to predict time-frequency task responses and their variability in human subjects based on resting state data is highly attractive. Potentially, this might be very useful in a clinical setting. For fMRI, the potential clinical usefulness of task-free neuroimaging has already been demonstrated by predicting the location of language-relevant areas in patients from rest and its feasibility for pre-surgical planning (Parker Jones, Voets, Adcock, Stacey and Jbabdi, 2017). This suggests that something similar might be achieved with M/EEG in a clinical context. The dominating device in clinical settings is the EEG (and sensor-based analysis), but a similar approach as the one presented here for MEG source data should be feasible for EEG as well.

In conclusion, we believe that the framework presented here helps to better understand, model and predict inter-subject variability of task responses. Combined with the work of Tavor et al. (2016), our results suggest that spatial and spectral individual variability is a somewhat stable feature, inherent to an individual's brain.

CRediT authorship contribution statement

R. Becker: Conceptualization, Methodology, Software, Visualization. **D. Vidaurre:** Methodology, Software. **A.J. Quinn:** Software, Visualization. **R.G. Abeysuriya:** Software, Visualization. **O. Parker Jones:** Visualization. **S. Jbabdi:** Visualization. **M.W. Woolrich:** Conceptualization, Supervision, Methodology, Software.

Acknowledgments

The Wellcome Centre for Integrative Neuroimaging is supported by core funding from the Wellcome Trust (203139/Z/16/Z). MWW's research is supported by the NIHR Oxford Health Biomedical Research Centre, by the Wellcome Trust (106183/Z/14/Z), and the MRC UK MEG Partnership Grant (MR/K005464/1). Data were provided by the Human Connectome Project, WU-Minn Consortium (Principal Investigators: David Van Essen and Kamil Ugurbil; 1U54MH091657) funded by the 16 NIH Institutes and Centers that support the NIH Blueprint for Neuroscience Research; and by the McDonnell Center for Systems Neuroscience at Washington University. We would also like to thank Dr. Alexis Hervais-Adelman for helpful comments regarding the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuroimage.2020.116818.

References

Arieli, A., Sterkin, S., Grinvald, A., Aertsen, A., 1996. Dynamics of ongoing activity: explanation of the large variability in evoked cortical responses. Science-AAAS-Weekly Paper Edition 273 (5283), 1868–1870.

Baker, A.P., Brookes, M.J., Rezek, I.A., Smith, S.M., Behrens, T., Probert Smith, P.J., Woolrich, M., 2014. Fast transient networks in spontaneous human brain activity. eLife 3, e01867. https://doi.org/10.7554/eLife.01867.

Becker, R., Ritter, P., Villringer, A., 2008. Influence of ongoing alpha rhythm on the visual evoked potential. Neuroimage 39 (2), 707–716.

Becker, R., Pefkou, M., Michel, C.M., Hervais-Adelman, A.G., 2013. Left temporal alpha-band activity reflects single word intelligibility. Front. Syst. Neurosci. 7 https://doi.org/10.3389/fnsys.2013.00121.

Biswal, B., Yetkin, F.Z., Haughton, V.M., Hyde, J.S., 1995 Oct. Functional connectivity in the motor cortex of resting human brain using echo-planar MRI. Magn. Reson. Med. 34 (4), 537–541.

Busch, N.A., Dubois, J., VanRullen, R., 2009. The phase of ongoing EEG oscillations predicts visual perception. J. Neurosci.: Off. J.Soc. Neurosci. 29 (24), 7869–7876. https://doi.org/10.1523/JNEUROSCI.0113-09.2009.

Colclough, G.L., Brookes, M.J., Smith, S.M., Woolrich, M.W., 2015. A symmetric multivariate leakage correction for MEG connectomes. Neuroimage 117, 439–448.

Colclough, G.L., Smith, S.M., Nichols, T.E., Winkler, A.M., Sotiropoulos, S.N., Glasser, M.F., et al., 2017. The heritability of multi-modal connectivity in human brain activity. eLife 6.

Cole, M.W., Ito, T., Bassett, D.S., Schultz, D.H., 2016. Activity flow over resting-state networks shapes cognitive task activations. Nat. Neurosci. 19 (12), 1718–1726.

Hunyadi, B., Woolrich, M.W., Quinn, A.J., Vidaurre, D., De Vos, M., 2019. A dynamic system of brain networks revealed by fast transient EEG fluctuations and their fMRI correlates. Neuroimage 185, 72–82.

Klimesch, W., 1997. EEG-alpha rhythms and memory processes. Int. J. Psychophysiol. : Off. J.Int. Organ.Psychophysiol. 26 (1–3), 319–340.

Klimesch, W., 1999. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. *Brain Research*. Brain Res. Rev. 29 (2–3), 169–195.

Larson-Prior, L.J., Oostenveld, R., Penna Della, S., Michalareas, G., Prior, F., Babajani-Feremi, A., et al., 2013. Adding dynamics to the human connectome Project with MEG. Neuroimage 80, 190–201.

Lee, J.-H., Hashimoto, R., Wible, C.G., Yoo, S.-S., 2011. Investigation of spectrally coherent resting-state networks using non-negative matrix factorization for functional MRI data. Int. J. Imag. Syst. Technol. 21 (2), 211–222.

Maguire, E.A., Gadian, D.G., Johnsrude, I.S., Good, C.D., Ashburner, J., Frackowiak, R.S., Frith, C.D., 2000. Navigation-related structural change in the hippocampi of taxi drivers. Proc. Natl. Acad. Sci. Unit. States Am. 97 (8), 4398–4403. https://doi.org/10.1073/pnas.070039597.

Mathewson, K.E., Gratton, G., Fabiani, M., Beck, D.M., Ro, T., 2009. To see or not to see: prestimulus phase predicts visual awareness. J. Neurosci. : Off. J.Soc. Neurosci. 29 (9), 2725–2732. https://doi.org/10.1523/JNEUROSCI.3963-08.2009.

Mazaheri, A., Jensen, O., 2008. Asymmetric amplitude modulations of brain oscillations generate slow evoked responses. J. Neurosci. : Off. J.Soc. Neurosci. 28 (31), 7781–7787. https://doi.org/10.1523/JNEUROSCI.1631-08.2008.

Nikulin, V.V., Linkenkaer-Hansen, K., Nolte, G., Lemm, S., Müller, K.R., Ilmoniemi, R.J., Curio, G., 2007. A novel mechanism for evoked responses in the human brain. Eur. J. Neurosci. 25 (10), 3146–3154. https://doi.org/10.1111/j.1460-9568.2007.05553.x.

O'Neill, G.C., Tewarie, P.K., Colclough, G.L., Gascoyne, L.E., Hunt, B.A.E., Morris, P.G., et al., 2017. Measurement of dynamic task related functional networks using MEG. Neuroimage 146, 667–678. https://doi.org/10.1016/j.neuroimage.2016.08.061.

Obleser, J., Weisz, N., 2012. Suppressed alpha oscillations predict intelligibility of speech and its acoustic details. Cerebr. Cortex 22 (11), 2466–2477.

Oostenveld, R., Fries, P., Maris, E., Schoffelen, J.-M., 2011. FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. Comput. Intell. Neurosci. 156869, 2011.

Parker Jones, O., Voets, N.L., Adcock, J.E., Stacey, R., Jbabdi, S., 2017. Resting connectivity predicts task activation in pre-surgical populations. NeuroImage. Clinical 13, 378–385. https://doi.org/10.1016/j.nicl.2016.12.028.

Pineda, J.A., 2005. The functional significance of mu rhythms: translating "seeing" and "hearing" into "doing". *Brain Research*. Brain Res. Rev. 50 (1), 57–68.

Porcaro, C., Zappasodi, F., Rossini, P.M., Tecchio, F., 2009. Choice of multivariate autoregressive model order affecting real network functional connectivity estimate. Clin. Neurophysiol. 120 (2), 436–448. https://doi.org/10.1016/j.clinph.2008.11.011.

Quinn, A.J., Vidaurre, D., Abeysuriya, R., Becker, R., Nobre, A.C., Woolrich, M.W., 2018. Task-evoked dynamic network analysis through hidden markov modeling. Front. Neurosci. 12, 603. https://doi.org/10.3389/fnins.2018.00603et al, 2018.

Seghier, M.L., Price, C.J., 2018. Interpreting and utilising intersubject variability in brain function. Trends Cognit. Sci. 22 (6), 517–530. https://doi.org/10.1016/j.tics.2018.03.003.

Shen, X., Finn, E.S., Scheinost, D., Rosenberg, M.D., Chun, M.M., Papademetris, X., Constable, R.T., 2017a. Using connectome-based predictive modeling to predict individual behavior from brain connectivity. Nat. Protoc. 12 (3), 506–518. https://doi.org/10.1038/nprot.2016.178.

Shen, X., Finn, E.S., Scheinost, D., Rosenberg, M.D., Chun, M.M., Papademetris, X., Constable, R.T., 2017b. Using connectome-based predictive modeling to predict individual behavior from brain connectivity. Nat. Protoc. 12 (3), 506–518.

Shin, H., Law, R., Tsutsui, S., Moore, C.I., Jones, S.R., 2017. The rate of transient beta frequency events predicts behavior across tasks and species. eLife 6, 572.

Smith, S.M., Nichols, T.E., Vidaurre, D., Winkler, A.M., Behrens, T.E.J., Glasser, M.F., et al., 2015. A positive-negative mode of population covariation links brain connectivity, demographics and behavior. Nat. Neurosci. 18 (11), 1565–1567.

Srinivasan, R., Winter, W.R., Nunez, P.L., 2006. Source analysis of EEG oscillations using high-resolution EEG and MEG. Prog. Brain Res. 159, 29–42.

Tavor, I., Parker Jones, O., Mars, R.B., Smith, S.M., Behrens, T.E., Jbabdi, S., 2016. Task-free MRI predicts individual differences in brain activity during task performance. Science 352 (6282), 216–220.

van Ede, F., Quinn, A.J., Woolrich, M.W., Nobre, A.C., 2018. Neural oscillations: sustained rhythms or transient burst-events? Trends Neurosci. 41 (7), 415–417.

Van Essen, D.C., Smith, S.M., Barch, D.M., Behrens, T.E.J., Yacoub, E., Uğurbil, K., WU-Minn HCP Consortium, 2013. The Wu-minn human connectome Project: an overview. Neuroimage 80, 62–79. https://doi.org/10.1016/j.neuroimage.2013.05.041.

Vidaurre, D., Hunt, L.T., Quinn, A.J., Hunt, B.A.E., Brookes, M.J., Nobre, A.C., Woolrich, M.W., 2018a. Spontaneous cortical activity transiently organises into frequency specific phase-coupling networks. Nat. Commun. 9, 2987.

Vidaurre, D., Quinn, A.J., Baker, A.P., Dupret, D., Tejero-Cantero, A., Woolrich, M.W., 2016. Spectrally resolved fast transient brain states in electrophysiological data. Neuroimage 126, 81–95.

Vidaurre, D., Smith, S.M., Woolrich, M.W., 2017. Brain network dynamics are hierarchically organized in time. Proc. Natl. Acad. Sci. U.S.A. 19, 201705120.

Vidaurre, D., Abeysuriya, R., Becker, R., Quinn, A.J., Alfaro-Almagro, F., Smith, S.M., Woolrich, M.W., 2018b. Discovering dynamic brain networks from big data in rest and task. Neuroimage 180, 646–656.

Woolrich, M., Hunt, L., Groves, A., Barnes, G., 2011. MEG beamforming using Bayesian PCA for adaptive data covariance matrix regularization. Neuroimage 57 (4), 1466–1479.

Zich, C., Woolrich, M.W., Becker, R., Vidaurre, D., Scholl, J., Hinson, E.L., et al., 2018. Motor learning shapes temporal activity in human sensorimotor cortex. BioRxiv. https://doi.org/10.1101/345421.

Abeysuriya R.G., Hadida J., Sotiropoulos S.N., Jbabdi S., Becker R., Hunt B.A.E., Brookes M.J., Woolrich M.W, 2018 Feb 23. A biophysical model of dynamic balancing of excitation and inhibition in fast oscillatory large-scale networks. PLoS Comput Biol. 14(2): e1006007. doi: 10.1371/journal.pcbi.1006007. eCollection 2018 Feb.

Hadida J, Sotiropoulos SN, Abeysuriya RG, Woolrich MW, Jbabdi, Bayesian Optimisation of Large-Scale Biophysical Networks. S.Neuroimage. **2018** Jul 1;174:219-236. doi: 10.1016/j.neuroimage.**2018**.02.063. Epub **2018** Mar 6.