Information-Guided dynamic functional connectivity for task phase prediction in fMRI

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Introduction

Dynamic functional connectivity (dFC) modulated by Hidden Markov Models (HMMs) is commonly used to identify time-dependent brain states in task fMRI [1]. A natural question arises: can we use dFC to recover the task phase? In other words, we are addressing the state–task correspondence problem. However, this question is difficult to answer even for very simple tasks such as finger tapping [2]. The main challenge is that HMMs are typically trained in an unsupervised manner. Furthermore, traditional HMMs treat each subject independently. As a result, the model cannot leverage information shared across subjects, even though they typically follow the same task design. Prior work using this approach has therefore reported limited accuracy [2]. Some studies have proposed alternative approaches based on neural networks and implemented supervised training. While this setup can easily encode task information and achieve relatively high accuracy, it offers limited interpretability [3]. In this abstract, we show that by incorporating additional information into the system, the HMM can learn the task phase with high accuracy even for a complex task such as pattern separation.

The assumptions about this problem are listed below. First, brain states are dynamically connected over the time domain, and time-dependent models perform better by using temporal ordering information. Second, incorporating task phases into dFC training can help improve accuracy. Third, all data are assumed to share the same task-phase progression across time. Fourth, to distinguish between task fMRI and the HMM, we use phase for the task and state for the HMM. As a result, we consider four hidden states to match the four task phases in our design. Fifth, to simplify the problem, we do not perform data separation. Consequently, all reported accuracies are training accuracy.

Dataset

The imaging data were acquired on a 7T Siemens MAGNETOM Terra MR scanner and included 46 cognitively normal subjects and 41 subjects with mild cognitive impairment (MCI) [4]. Each subject underwent 1–3 fMRI scans, yielding a total of 235 scans. The functional MRI runs were collected using a multiband gradient-echo EPI sequence with TR = 1530 ms. All subjects underwent preprocessing, including slice-timing correction, realignment, and normalization to MNI space. The fMRI data were denoised by regressing out CSF and gray-matter signals and then parcellated into 32 regions using the CONN-32 atlas (https://web.conn-toolbox.org/). For each region, the meantime series was extracted, yielding a 32-dimensional representation. We considered only the non-encoding phase, with 292 time points. The task is binary encoded and convolved with the Hemodynamic Response Function (HRF). The task phases are distraction, repeat, lure, and new. The HRFs were first normalized to unit standard deviation and were further normalized using cross-entropy. Finally, the data have size 235 × 292 × 32, with task information (\delta) of size 292 × 4.

Model

In the traditional generative model, for subject (s), observations at time (t) are generated using a Gaussian distribution with mean (\mu) and covariance (\sigma), with the definition shown in Figure 1. Purely unsupervised learning may not yield sufficient accuracy, so we consider incorporating additional information into the system. The first type of information we consider is the temporal relationship, abbreviated as time. In the time-independent model, observations at each time point are described by a Gaussian with a mean and covariance, and the state occupancy probability is computed directly from this Gaussian. In the time-dependent model, the temporal ordering is considered through transition probability. The state occupancy probability follows HMM, with both forward and backward probabilities used.

The second type of information we consider is task-awareness. Without task information, the system is purely unsupervised; with task information, the system becomes supervised. The unsupervised model starts from random initial conditions, use the Expectation–Maximization (EM) algorithm to estimate the parameters, and finally compute the state occupancy probability. The supervised model uses (\delta) as the initial state occupancy probability to estimate the parameters and then fixes the parameters to update the occupancy probabilities.

The third type of information concerns how to encode the assumption that all subjects follow the same task at each time point. Previous setups did not fully use this information. For example, in [2], occupational probabilities are first computed individually and then averaged at the subject level. This does not fully exploit the shared information because, during training, different subjects are still treated separately. In this abstract, we incorporate shared design information through the weighted-sharing idea proposed in [5]. We consider (\delta_{tk}) with dimension (235 \times 4), representing the weights across all subjects and time points. We assume that, for each subject at time (t) and state (k), the emission probability is a mixture of two Gaussians weighted by (\delta_{tk}). The advantage of this model is that, instead of placing constraints directly on (\gamma), it is much easier to put constraints on Gaussian mixture. Second, all algorithms are defined using the Expectation–Maximization (EM) framework. From an interpretability perspective, (\sigma_1 - \sigma_2) represents the features that drive the model to assign data to different states.

The three types of information are completely independent, which means each model can include none, some, or all three. For example, for configuration 1, no information is used: this is just a Gaussian mixture with 4 states, and all states are estimated using the EM algorithm. Configuration 2 uses only time information, corresponding to an HMM with hidden states (K=4), which is the same setup as in previous work [2]. For configuration 3, task-aware information is used: we first train the model using the ground truth (\delta=\gamma) for the Gaussian mixture to estimate the means and covariances, then fix the means and covariances to obtain the predicted \gamma. For configuration 4, only shared-design information is used: we assume all subjects follow the weighted HMM proposed in Figure 1, but we do not input the real \delta into the model, similar idea is shown in [5]. The same idea can be extended to configurations where more than one type of information is used. Finally, we have one model where all three types of information are included.

All configurations are trained using EM algorithms. To avoid local minima, 100 initial conditions are used, and the one that leads to the maximum likelihood is selected. For configurations with task information, the state-phase correspondence is exact, and we directly evaluate the Mean Square Error (MSE) from the system. For configurations without task information, we generate permutations for the states and choose the one that leads to the smallest MSE.

Result

Specifically, first, among the 8 configurations, configuration 3 does not need iterative training, because once the probabilities are given for a Gaussian mixture, all properties of the system are fixed. We note that even when we input the ground truth into the system, the resulting model can still be a mixture due to the large noise in the data. Second, as the prediction phase for the weights is also iterative, for configurations 5, 7, and 8, the predicted \delta starts from 0.5 and runs iterations until the model converges. Third, for models with shared-design, \delta can be treated directly as the prediction, but for models without shared-design, we average the state occupancy probabilities across all subjects as the predicted \delta.

Figure 2 (a) shows the MSE selected from the maximum likelihood for the 8 different configurations. We find that the most important information in this problem is task-aware, which meets our expectations. We also note that for the configuration with all three types of information, the MSE is the smallest. In Figure 2 (b), we plot the real and predicted \delta in this case. Except for the repeat phase, the other three phases yield reasonable predictions. In Figure 2 (c), we show the covariance matrices for \sigma_1 and \sigma_2 and their difference. One observation is that the difference is almost reversed between the distraction phase and the lure phase. Since the repeat phase has a relatively large error, the differences for that phase may not reflect the true underlying pattern.

In conclusion, in this abstract we analyze the correspondence between HMM states and task fMRI phases. By setting the number of hidden states equal to the number of task phases, we find that the model incorporating time, task-aware, and shared-design information yields the smallest MSE. Although the reported accuracy is all training accuracy, the use of dFC provides strong interpretability, and all results are based solely on the generative model. Practical applications of this method include predicting task phases from fMRI time series and identifying potential relationships between behavioral performance and brain states.

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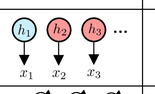
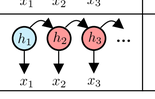
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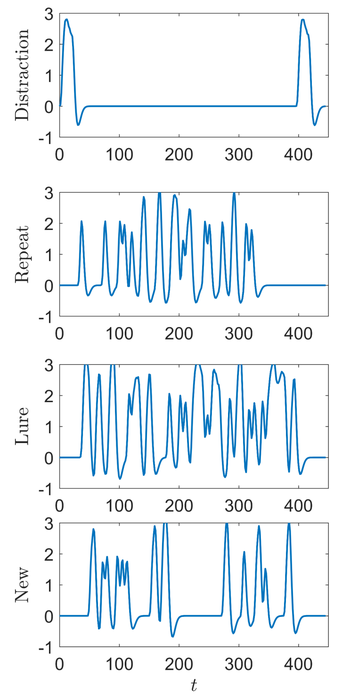
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Figure 1

(a)

Usage \ Information	Time	Task-Aware	Shared-Design
No		Unsupervised	$P_{stk} = \frac{1}{(2\pi)^{p/2}\lvert\sigma_k\rvert^{-1/2}} \times \exp\left[-\frac{1}{2}(x_{st}-\mu_k)\sigma_k^{-1}(x_{st}-\mu_k)\right]$
Yes		Supervised	$P_{stk} = \delta_{tk}P^{(1)}_{stk} + (1-\delta_{tk})P^{(2)}_{stk}$, $\delta_{tk} = \sum_s \frac{\gamma_{stk}}{N} \frac{\delta_{tk}P^{(1)}_{stk}}{\delta_{tk}P^{(1)}_{stk} + (1-\delta_{tk})P^{(2)}_{stk}}$

(b)



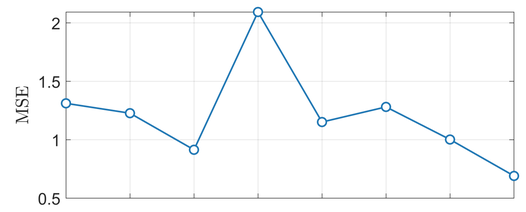
(c)

Subject index	s	Observation	$x_{st} \in \Re^{1\times p}$
Number of subjects	N	State occupational probability	γ_{skt}
Feature index	p	Task weight	δ_{tk}
Hidden state index	k	Normal distribution	$\mathcal{N}(\mu_k, \sigma_k)$
Time index	t		

Figure 1: (a) Three types of information considered—time, task-aware, and shared-design. Each type can be included or excluded in a configuration, generating eight possibilities. (b) HRF responses for four phases in pattern separation. (c) Definition of the Weighted HMM. The task weight δ_{tk} is shared across subjects.

Figure 2

(a)

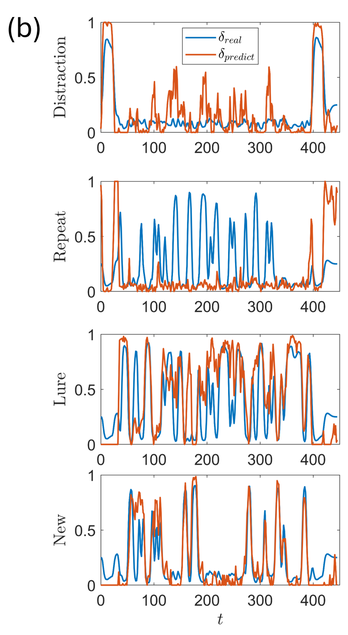


1	2	3	4	5	6	7	8	Configuration
No	Yes	No	No	Yes	Yes	No	Yes	Time
No	No	Yes	No	Yes	No	Yes	Yes	Task-Aware
No	No	No	Yes	No	Yes	Yes	Yes	Shared-Design

8 network categories

Default Mode (DMN)
Sensorimotor (SM)
Visual (VIS)
Salience (SN)
Dorsal Attention (DAN)
Frontoparietal (FPN)
Language (LAN)
Cerebellar (CB)

(b)



(c)

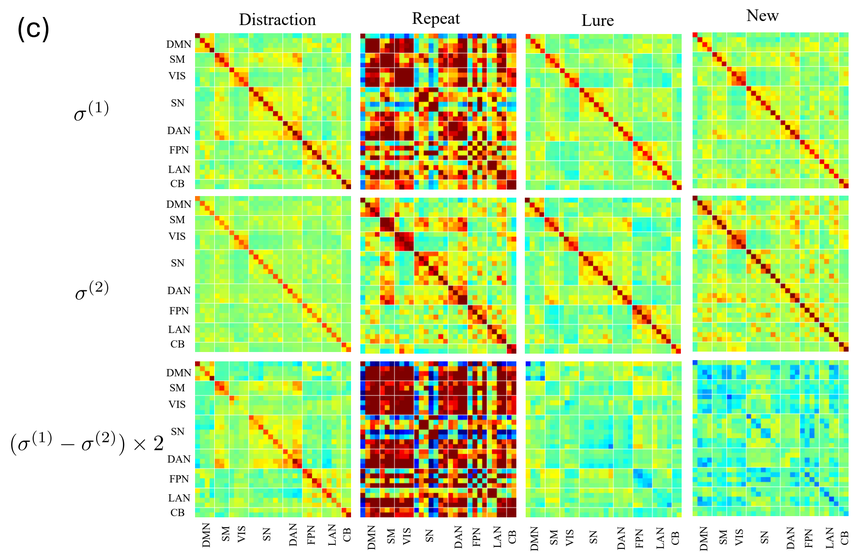


Figure 2: (a) MSE for eight different configurations. Task-Aware is proven to be the most important factor for prediction. The minimum MSE appears in the configuration with Time-Dependent, Task-Aware, and Shared-Design. (b) The predicted and real δ for configuration 8. (c) The covariance matrices and their difference for configuration 8. The difference indicates which networks help distinguish the states.