Assessing Frequency-Dependent Behavior Predictability via Coherence-based Fingerprinting

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Introduction

Leveraging vast resting-state functional MRI (rsfMRI) data and machine learning, individual-level rsfMRI-based brain connectivity, especially the functional connectome, as reliable in capturing individual behavioral differences (Finn et al. 2015, Beaty et al. 2018, Nostro et al. 2018). Despite its limited frequency bandwidth (0.01-0.20 Hz (Niazy et al. 2011, Yuen et al. 2019)), rsfMRI signals show a diverse spectral distribution in the human cortex (Fox & Raichle 2007), prompting the question of whether these spectral differences influence intrapersonal behavior prediction. We propose the Coherence-based Predictive Modeling (CoPM), using spectrally rich functional coherence features to explore this spectral-behavior relationship.

Our application of CoPM to Human Connectome Project rsfMRI data (Van Essen et al. 2013) reveals that functional coherence features' frequency significantly impacts behavior predictability. Median-frequency features ($0.022 - 0.113$ Hz) outperform low ($0.020 - 0.031$ Hz) and high-frequency ($0.090 - 0.171$ Hz) ranges in intrapersonal fingerprinting. The spectral similarity of these features aligns with their predictive accuracy across behavior domains, highlighting a strong spectral-behavior relationship and underscoring CoPM's potential in elucidating the brain-behavior relationship through spectral analysis.

Methods: Coherence-based Predictive Modeling (CoPM)

The proposed coherence-based predictive model (CoPM) aims to evaluate the predictive performance of frequency-specialized coherence features across a range of behavior items and domains. The methodology of CoPM is structured into a three-stage pipeline as follows: (A) the brain-wide coherence feature extraction, (B) the frequency-dependent coherence profiling, (C) the predictive model construction. A graphical representation of this pipeline is illustrated in Figure 1.

Dataset: HCP rsfMRI data with behavior items

We utilized the preprocessed resting-state functional MRI (rsfMRI) data from the Human Connectome Project (HCP), which involved data from 400 subjects (Van Essen et al. 2013). For extracting the region-of-interest (ROI) time series from each individual's rsfMRI data, we employed the Power parcellation atlas (Power et al. 2011). To assess behavioral aspects, we selected 43 items spanning across five behavioral domains: cognition, sensory-motor function, emotion, psychological well-being, and personality. The distribution of these items across the domains is outlined in Table 1.

CoPM Stage-A: Brain-wide coherence feature extraction

In the initial stage of the CoPM, our focus is on generating brain-wide functional coherence features for each individual. To achieve this, we primarily utilized the temporal de-correlation (TD) method (Bai & Yoshimoto 2021), enhancing the spectral resolution of HCP rsfMRI data. We define the functional coherence $Coh(i, j)$

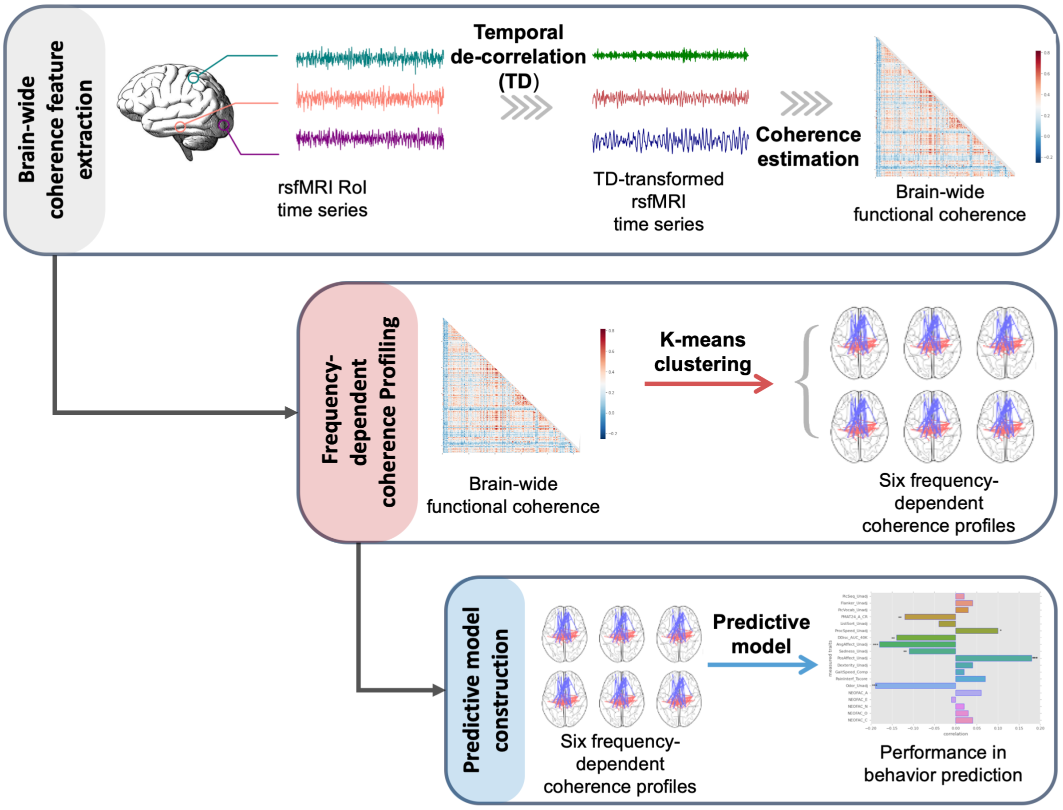

Figure 1: **Workflow of CoPM.** CoPM undergoes three processing steps as follows. In the first step, coherence feature extraction (indicated by the grey shaded box), we apply the temporal de-correlation (TD) approach to the rsfMRI signal to obtain individual-level TD-transformed time series. Subsequently, brain-wide coherence features are estimated using Eq.1. The second step (highlighted in the red shaded box) involves applying the K-means clustering method to the previously extracted coherence features. This process is used to derive six frequency-dependent coherence profiles for each individual, ensuring a roughly equal number of coherence features in each profile. The final step (represented by the blue shaded box) focuses on building predictive models. These models are designed to assess the predictive performance of these coherence profiles across forty-three behavioral items.

Table 1: **Item-Domain relation in HCP data**

Domain	Items
cognition (12/43)	Flanker_Unadj, PicSeq_Unadj, PMAT24_A_CR, PMAT24_A_SI, PMAT24_A_RTCR, ReadEng_Unadj, PicVocab_Unadj, ProcSpeed_Unadj, IWRD_TOT, IWRD_RTC, ListSort_Unadj, DDisc_AUC_40K
emotion (11/43)	ER40HAP, ER40NOE, ER40ANG, ER40FEAR, ER40SAD, AngAffect_Unadj, AngHostil_Unadj, AngAggr_Unadj, FearAffect_Unadj, FearSomat_Unadj, Sadness_Unadj,
(psychological) well-being (11/43)	LifeSatisf_Unadj, MeanPurp_Unadj, PosAffect_Unadj, Friendship_Unadj, Loneliness_Unadj, PercHostil_Unadj, PercReject_Unadj, EmotSupp_Unadj, InstruSupp_Unadj, PercStress_Unadj, SelfEff_Unadj
sensory-motor functions (4/43)	Dexterity_Unadj, Odor_Unadj, PainInterf_Tscore, GaitSpeed_Comp
personality (5/43)	NEOFAC_A, NEOFAC_O, NEOFAC_C, NEOFAC_N, NEOFAC_E

between the multi-taper estimated power spectra of two TD-transformed time series y_i and y_j as follows:

$$Coh(i,j) = \frac{|y_{ij}^{mt}(f)|^2}{y_i^{mt}(f) y_j^{mt}(f)}, \tag{1}$$

where $y_{ij}^{mt}(f)$ is the cross power spectral density of signals y_i and y_j (Sun et al. 2005). This analysis was conducted across all cortical regions to derive the brain-wide functional coherence features for all subjects.

CoPM Stage-B: Frequency-dependent coherence profiling

Armed with derived functional coherence features for each individual, we proceeded to cluster these features based on their frequency characteristics. Utilizing the K-means clustering method, we formed six distinct clusters, resulting in six frequency-dependent coherence profiles for each individual, as outlined in Table 2. To ensure fair comparisons, we maintained an equal number of features in each profile. The frequency statistics were used to categorize the profiles: profile-1 and -2 were classified as high-frequency profiles, profiles-3, -4, -5 as median-frequency profiles, and profile-6 as the low-frequency profile.

Table 2: **Frequency statistics of 6 coherence profiles**

Coherence profile	Mean frequency(Hz)	Range(Hz)
profile-1	0.123	[0.090, 0.158]
profile-2	0.154	[0.139, 0.171]
profile-3	0.082	[0.064, 0.113]
profile-4	0.025	[0.020, 0.031]
profile-5	0.035	[0.022, 0.045]
profile-6	0.025	[0.020, 0.031]

CoPM Stage-C: Predictive model construction

In the final stage of CoPM, we adopted an approach similar to the methodology used in functional connectome-based predictive modeling Shen et al. (2017). Our goal was to develop a predictive model capable of evaluating the behavioral predictability of profile-wise coherence features. This development process was executed through the designed four-step process:

1. Formation of Prediction Feature Sets.
   We employed Pearson correlation to link coherence features with each of the 43 behavior items targeted for prediction.

2. Selection of Coherence Features.
   Only highly correlated coherence features, which were determined by pre-defined criteria (the statistical significant positive and negative correlations with $p < 0.5$.), were allowed to enter the prediction feature sets. For each coherence profile, the gathered prediction features were further concatenated into the summary statistics for every subject in the pool.

3. Construction of the Predictive Model.
   These conservative subject-wise summary statistics were served as the final prediction features x to fit a linear model, i.e., $y = \beta x + \epsilon$, where dependent variables y are the included behavior items.

4. Evaluation of Predictive Performance.
   The model's predictive ability was tested on hold-out subjects (x_{new}), producing predicted behavior measures y_{new} via $y_{new} = \beta x_{new} + \epsilon$. The predictive utility of the coherence features was assessed using the Pearson's correlation value, determined through empirical null distribution via 1000 permutations in permutation testing.

Beyond assessing the predictive utility for each behavior item, we also explored the correlation between profile-wise spectral and prediction similarities across five behavioral domains. For each profile, we binarized the prediction patterns of coherence features on behavior items, coding significant predictions as 1 (inclusive of both significant positive and negative correlations) and non-significant ones as 0. The dice coefficient was used to measure the prediction similarity between profiles. Following this, we conducted a correlation analysis to examine the relationship between the spectral similarity of coherence profiles and their respective prediction patterns in various behavior domains.

Results

Upon applying the proposed Coherence-based Predictive Model (CoPM) to the HCP rsfMRI data, our initial observation highlighted the discriminative capability of functional coherence features in identifying intrapersonal behavioral differences, regardless of their frequency. Notably, within the predicted behaviors, psychological well-being emerged as unique, being consistently predicted across all six coherence profiles. This suggests that brain signatures related to well-being may encompass a broad spectral range. Similarly, the personality domain showed predictions across a wide frequency bandwidth, albeit with the exception of the low-frequency profile-6. In contrast, successful predictions for the emotion domain were predominantly associated with the median-frequency coherence features (as shown in Figure 2(a))

The predictive performance varied among the six frequency-dependent coherence profiles, thereby illuminating the spectral-behavior relationship in behavior prediction. Profile-2, which encompasses high-frequency coherence features, exhibited the lowest prediction performance. On the other hand, the median-frequency coherence features in profiles 3, 4, and 5 demonstrated superior predictive utility, covering a broader range of behavior domains with a greater number of predicted behavior items.

This frequency-dependent prediction was further evident when evaluating the similarity between profile-wise rhythmic (e.g., frequency) characteristics and the prediction patterns. A strong positive correlation was identified (Pearson's $r = 0.606, p < 0.001$; Figure 2(b)), suggesting that the utilized functional coherence features are frequency-dependent in predicting intrapersonal behavior.

Conclusions

The ubiquity of rsfMRI recordings and advancements in machine learning techniques have positioned individual-level cortico-cortical connections, such as the functional connectome, as key discriminators for identifying intrapersonal differences across various behavioral domains. Given that cortical regions across the brain exhibit a spectral distribution, there is growing interest in examining the spectral bias of these brain signatures in behavior prediction. A major challenge in this pursuit is the inherently low frequency resolution of rsfMRI signals, which has limited the reliability of the commonly used functional connectome as a spectral-based predictor in behavior analysis. To address this, our study introduces the Coherence-based Predictive Modeling (CoPM), a novel pipeline designed to leverage the spectrally rich functional coherence features in examining the frequency-dependent predictability across multiple behavior domains.

When applied to HCP rsfMRI data, CoPM demonstrates its ability to discern individual differences across diverse behavioral domains through frequency-dependent functional coherence features. By examining spectral variances in these features, CoPM reveals that the predictability of behavioral outcomes from coherence features is contingent upon their frequency. These insights pave the way for future applications of CoPM in various neuroimaging datasets, such as those pertaining to neuropsychiatric disorders, to harness the potential of spectrally rich functional coherence features in the field of computational psychiatry.

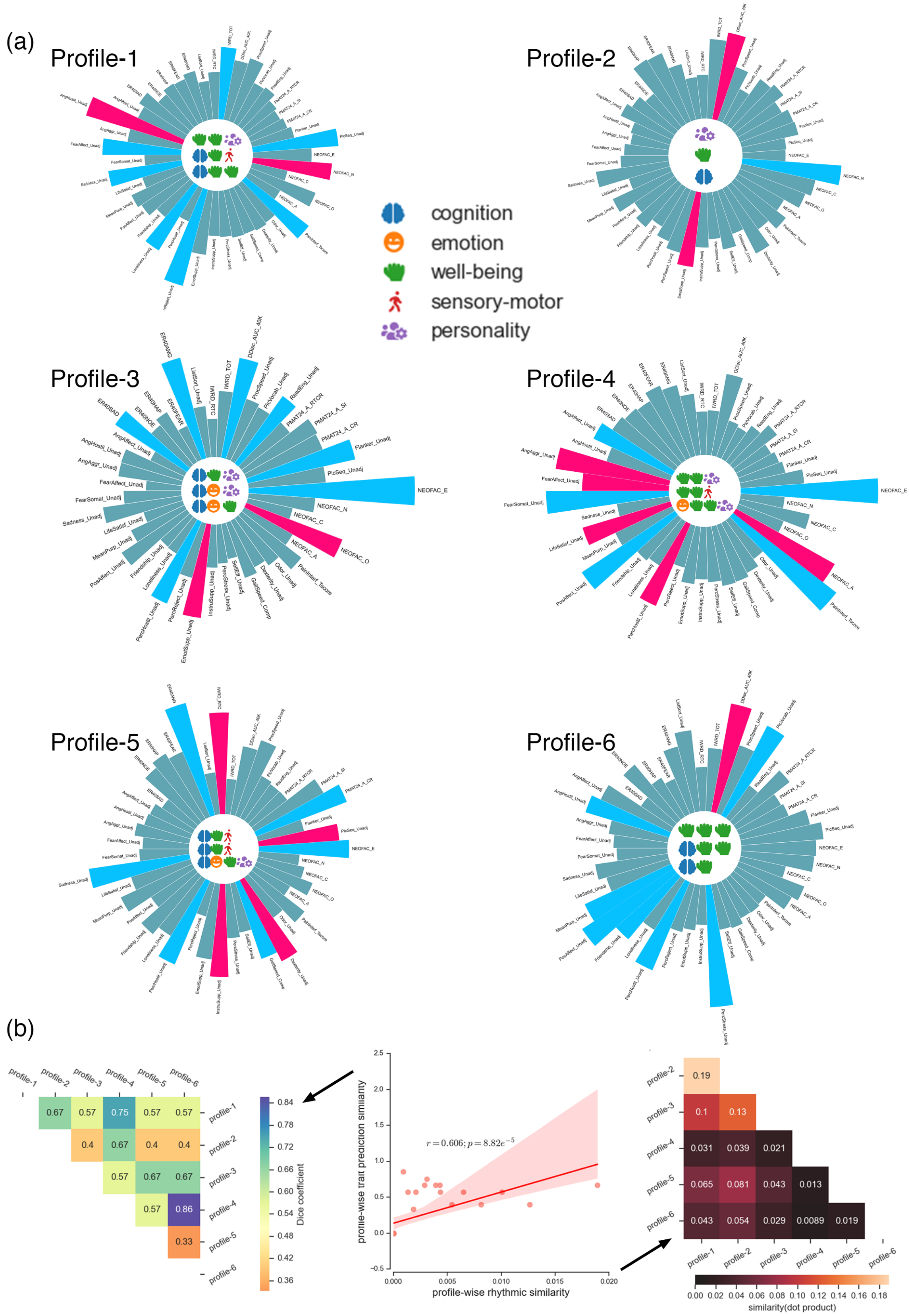
(a)
Profile-1
Profile-2
Profile-3
Profile-4
Profile-5
Profile-6
cognition
emotion
well-being
sensory-motor
personality
(b)
profile-1
profile-2
profile-3
profile-4
profile-5
profile-6
0.67 0.57 0.75 0.57 0.57
0.4 0.67 0.4 0.4
0.57 0.67 0.67
0.57 0.86
0.33
Dice coefficient
0.84 0.78 0.72 0.66 0.60 0.54 0.48 0.42 0.36
profile-wise trait prediction similarity
profile-wise rhythmic similarity
r = 0.606; p = 8.82e−5
0.19
0.1 0.13
0.031 0.039 0.021
0.065 0.081 0.043 0.013
0.043 0.054 0.029 0.0089 0.019
similarity(dot product)
0.00 0.02 0.04 0.06 0.08 0.10 0.12 0.14 0.16 0.18

Figure 2: **Frequency-dependent coherence profiles in predicting behavior items and domains.** (a) Varied performance of 6 coherence profiles in predicting intra-personal behavior domains. The highlighted bars in each of 6 circular bar-plots (profiles) indicate the significantly predicted behavior items, which red and blue colors represent the statistical significant positive and negative correlations $p < 0.05$. The icons that fill the inner circles of 6 circular bar-plots represent the predicted behavior domains. (b) The revealed correlational relation between the profile-wise resemblance in prediction patterns and the spectral similarity between profile-wise coherence features. Differences in prediction patterns are quantified in terms of their pair-wise dice coefficient, whereas the profile-wise spectral similarity is computed via the dot product (cosine similarity) between mean frequencies of profiles.

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