# Assessing Functional Neural Connectivity as an Indicator of Cognitive Performance*

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**Abstract.** Studies in recent years have demonstrated that neural organization and structure impact an individual's ability to perform a given task. Specifically, more efficient functional networks have been shown to produce better performance. We apply this principle to evaluation of a working memory task by providing two novel approaches for characterizing functional network connectivity from electroencephalography (EEG). Our first approach represents functional connectivity structure through the distribution of eigenvalues making up channel coherence matrices in multiple frequency bands. Our second approach uses a connectivity matrix at each frequency band, assessing variability in average path lengths and degree across the network. We also use features based on the pattern of frequency band power across the EEG channels. Failures in digit and sentence recall on single trials are detected using a Gaussian classifier for each feature set at each frequency band. The classifier results are then fused across frequency bands, with the resulting detection performance summarized using the area under the receiver operating characteristic curve (AUC) statistic. Fused AUC results of 0.63/0.58/0.61 for digit recall failure and 0.57/0.59/0.47 for sentence recall failure are obtained from the connectivity structure, graph variability, and channel power features respectively.

## 1 Introduction

Recent studies have investigated neural efficiency as a way of measuring an individual's ability to perform a specific task. Neural efficiency was examined by Neubauer, where he showed that individuals with a higher functional ability also showed lower event related desynchronizations [11] while performing the task. This principle has been employed along with network analysis to represent the changes in the properties of the functional connectivity network [6, 8, 9]. This has resulted in studies demonstrating increased task proficiency is exhibited by a network exhibiting more "small

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adfa, p. 1, 2011.

world" properties (i.e. where the network has a higher clustering coefficient and lower average shortest path length). In this paper, we examine changes in network properties during a working memory task, and provide a comparison using alternate approaches to characterizing network connectivity, and a non-network based approach that assess changes in power across a set of frequency bands.

## 2 Materials

This work leverages a previously collected database published in [1]. This database provides an IRB approved working memory protocol where subjects are asked to retain a series of digits, followed by a sentence in memory. After a pause period the subjects were asked to repeat the memorized sentence, and then to repeat the memorized digits. A trial was defined as the memorization and repetition of one sentence, and one set of digits. Performance was identified based on whether the subject could correctly repeat the entire sentence (sentence performance), and the entire sequence of digits (digit performance).

During this protocol, speech, video data, and electroencephalography (EEG), were collected. This paper presents an analysis of the predictive performance of EEG in identifying sentence performance and digit performance on a per trial basis. EEG was collected on 14 subjects, where each subjects' data were preprocessed with a highpass filter at 0.1 Hz, a notch filter at 60 Hz, and had blinks removed using independent component analysis.

## 3 Methods

### 3.1 Coherence as a Measure of Functional Connectivity

In order to obtain sensitive multivariate measures of frequency-band dependent communication between brain regions, we utilize features based on the full set of signal coherences obtained between channels within previously used neurologically representative frequency bands (theta, alpha, beta, gamma) [4]. The coherence between channels indicates the amount of cross-channel power in a frequency band relative to the amount of within-channel power. This provides a measure of how closely related the signals are within a given frequency band.

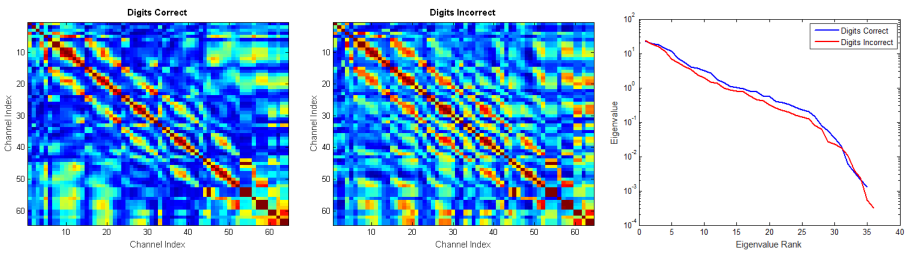

**Fig. 1.** Coherence matrices for the same subject on a trial with correct (left) and incorrect (middle) digit recall, (right) rank-ordered eigenvalues from the two coherence matrices.

Specifically, channel-pairwise coherences are computed to yield a 64x64 coherence matrix for each frequency band in each trial. Figure 1 shows, for example, coherence matrices (in the Theta band) from a single subject in two nearby trials from the middle of the subject's 2-hour session. The matrix on the left corresponds to a trial when the subject reported the four digits correctly, and the matrix on the right corresponds to a trial when they reported the digits incorrectly. There is a striking difference in the appearance of the two coherence matrices, with the incorrect trial showing a larger number of strong pairwise coherences.

### 3.2 Connectivity Structure

To obtain features that are sensitive to changes in the overall structure of coherences among EEG channels, while being invariant to the particularities of coherence patterns among specific channel pairs, we propose the use of coherence structure features [1]. Coherence structure refers to the distribution of eigenvalues in a coherence matrix, which encodes the overall shape of the multivariate coherence distribution, invariant to axis assignments. Figure 1 (right) plots the coherence structure features, which are the rank-ordered eigenvalues from the two coherence matrices, illustrating that the digits correct case (blue) produces greater power in the small matrix eigenvalues than the incorrect case (red), thereby indicating a more isotropic pattern of coherences during correct performance, which we take as an indicator of greater complexity in cortical communication.

The coherence structure patterns in Figure 1 depict two trials from a single subject. How do these patterns generalize to all the trials and subjects in the dataset? To answer this question, we first normalize (z-score) the eigenvalues at each rank across all the trials in the data set, and then plot in Figure 2 the average of these normalized eigenvalues for the digit correct (blue) and digit incorrect (red) cases for the four frequency bands. Figure 2 shows that a similar difference is found across all four frequency bands, with an interesting leftward shift in the eigenvalue differences as we move to higher frequency bands.

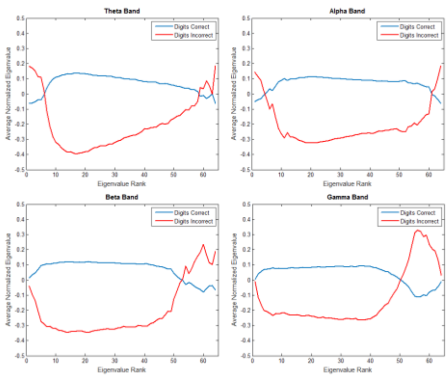

**Fig. 2.** Averages, computed across all trials, of normalized eigenvalues for digit correct (blue) and digit incorrect (red) recall in four frequency bands.

### 3.3 Graph Measures of Functional Connectivity

Recent work has considered network (or graph) features of brain activity. This section de-fines the construction process for the functional connectivity graph and the features used in the classifier.

A graph G=(V, E) is a pair of sets: a set of vertices, V, representing entities, and a set of edges, E, representing connections or interactions between the entities. In the context of this paper, the vertices are EEG channels and the edges denote functional synchrony between the channels. This is measured by coherence between the measurements in the channels, as described in Section 3.1.

The coherence values are stored in a matrix, which is thresholded to define undirected connections (E) between nodes (V). A set of thresholds are used, where each threshold is set to keep a constant density (as defined below). This approach builds off [7], where density is controlled to keep a similar number of connections across subjects. However, instead of using one threshold as done in [7], we aggregate features across thresholds and then use dimensionality reduction to remove redundancies.

After thresholding each coherence matrix to form a graph, the following features are extracted for classification.

**Density.** The proportion of possible edges that exist in the graph, $|E|/\binom{|V|}{2}$. This is used for normalization of the data: each graph has equal density.

**Average path length.** For a given vertex v, the average distance from v to any other vertex in the graph,

$$\ell(v) = \frac{1}{|V| - 1} \sum_{u \in V} d_G(v, u) \tag{1}$$

Average path length is small in small-world graphs.

**Degree.** The number of edges adjacent to a given vertex, denoted

$$k_v = |\{u \mid \{u, v\} \in E\}| \tag{2}$$

Small-world networks tend to have some “hub” vertices with high degree, to facilitate short paths through the network.

As in [2], we consider statistics of the vertex-based features (average path length, and degree) across all vertices in the graph. Specifically, we consider the maximum value, the mean, and the standard deviation. This provides information about the distribution of features across vertices without expanding the space to consider all features on all vertices. This information was reduced to the standard deviation of the above features, as it showed the most variability across trials. Figure 3 depicts differences in graph features as a function of frequency band summarized across correct and incorrect trials.

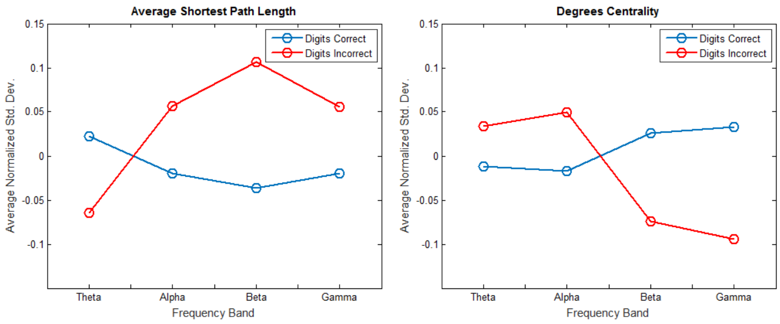


**Fig. 3.** Differences in graph features as a function of frequency band

# 4 Machine Learning Approach

## 4.1 Dimensionality Reduction via Principal Component Analysis.

The power and coherence structure feature sets are high dimensional, with 64 power and coherence structure features in each frequency band. The network features present complimentary information with some overlap across density thresholds. In order to obtain lower dimensional and less redundant features that can be easily utilized to detect digit and sentence recall failure, we use a common principal component analysis (PCA) dimensionality reduction procedure for each feature set. To avoid overfitting, we apply an identical procedure for each feature set by selecting the minimum number of principal component features needed to explain 90% of the total variance in the feature set.

## 4.2 Detecting Digit and Sentence Recall Failure.

For each subject, detection of digit recall failure is done using statistical models obtained solely from the other 13 subjects. The statistical models we use are multivariate Gaussian distributions for each feature set. The Gaussian classifier output for feature set in a given trial is a log-likelihood ratio of recall failure (Class 1) and recall success (Class 2). The results are summarized using the area under the receiver operating characteristic (ROC) curves, or AUC, for each feature set (Table 1). Fusion across feature sets is done by adding log-likelihood ratios. The fused power feature results combines only the classifier results from the Beta and Gamma bands, and the fused coherence structure and graph feature results combine results from all four bands.

# 5 Experimental Results

For this experiment we report prediction results obtained using leave one subject out cross validation. Table 1 displays the predictive ability of each set of features on identifying mistakes on the digit repetition portion of the experiment, and the sentence repetition portion of the experiment.

| Freq Band | Digit Failure AUC | | | Sentence Failure AUC | | |
|---|---|---|---|---|---|---|
| | Connect. Structure | Graph Var. | EEG Power | Connect. Structure | Graph Var. | EEG Power |
| Theta | 0.62 | 0.49 | 0.51 | 0.55 | 0.49 | 0.39 |
| Alpha | 0.57 | 0.54 | 0.45 | 0.60 | 0.54 | 0.40 |
| Beta | 0.60 | 0.57 | 0.60 | 0.57 | 0.57 | 0.41 |
| Gamma | 0.58 | 0.54 | 0.59 | 0.49 | 0.59 | 0.42 |
| Comb. | 0.63 | 0.58 | 0.61 | 0.57 | 0.59 | 0.47 |

**Table 1.** Number of principal components and area under ROC curves for power and coherence structure features at four frequency bands.

In our analysis, the power, graph, and structure features show similar performance on the digit recall task, with coherence structure consistently performing at or above the other two feature sets. However, the power features lose predictive ability on the the sentence failure task. Additionally, only a subset of bands are informative when combining across the three feature types. Through combining the three different feature sets, we were able to achieve a performance of 0.66 on the digit recall task, and 0.60 on the sentence recall task. The ROC curve for the digit recall task is shown below.

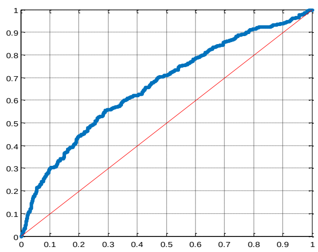

**Fig. 4.** Receiver operating characteristic (ROC) curve for best performing system, which fuses classifier outputs from power features in the Beta and Gamma bands, and from coherence structure and graph metrics in all four bands. AUC = 0.66.

## 6 Conclusion

In this paper we examined the use of features derived from network connectivity structure to predict performance on a digit and sentence recall task. Additionally, we compare our network features' performance to detection ability using simple power band features computed over equivalent frequency bands.

## References


1. Quatieri, Thomas F., et al. "Vocal Biomarkers to Discriminate Cognitive Load in a Working Memory Task." Sixteenth Annual Conference of the International Speech Communication Association. 2015.
2. Airoldi, E.M., Bai, X. & Carley, K.M. (2011) Network sampling and classification: An investigation of network model representations. *Decision Support Systems* **51**(3):506–518.
3. Watts, D.J. & Strogatz, S.H. (1998) Collective dynamics of 'small-world' networks. *Nature* **393**:440–442.
4. Micheloyannis, Sifis, et al. "Using graph theoretical analysis of multi channel EEG to evaluate the neural efficiency hypothesis." Neuroscience letters 402.3 (2006): 273-277.
5. Roux, Frédéric, and Peter J. Uhlhaas. "Working memory and neural oscillations: alpha–gamma versus theta–gamma codes for distinct WM information?." Trends in cognitive sciences 18.1 (2014): 16-25.
6. Bassett, Danielle Smith, and E. D. Bullmore. "Small-world brain networks." The neuroscientist 12.6 (2006): 512-523.
7. Stam, C. J., et al. "Small-world networks and functional connectivity in Alzheimer's disease." Cerebral cortex 17.1 (2007): 92-99.
8. Bullmore, Ed, and Olaf Sporns. "Complex brain networks: graph theoretical analysis of structural and functional systems." Nature Reviews Neuroscience 10.3 (2009): 186-198.
9. Bullmore, Ed, and Olaf Sporns. "The economy of brain network organization." Nature Reviews Neuroscience 13.5 (2012): 336-349.
10. Achard, Sophie, and Ed Bullmore. "Efficiency and cost of economical brain functional networks." PLoS Comput Biol 3.2 (2007): e17-e17.
11. Neubauer, Aljoscha C., and Andreas Fink. "Intelligence and neural efficiency." Neuroscience & Biobehavioral Reviews 33.7 (2009): 1004-1023.