Iowa Initiative for Artificial Intelligence

Final Report

Project title:	Generating a "Roadmap" for Transcranial Magnetic Stimulation Targeting: Using Functional and Structural Connectivity Patterns from MRI to Predict Intracranial EEG Evoked Potential Propagation Patterns Following Transcranial Magnetic Stimulation	
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Other investigators:		
Date:		
Were specific aims fulfilled:	Not as originally intended	
Readiness for extramural proposal?	No	
If yes … Planned submission date		
Funding agency		
Grant mechanism		
If no … Why not? What went wrong?	The ultimate goal of the original proposal was to try to use functional MRI data to predict the evoked responses of TMS pulses measured in various regions of the brain using intracranial EEG. Unfortunately, progress was significantly slower than expected due to a very complex dataset and multiple meetings required to get the team on the same page about the organization and interpretation of the data. These analyses below represent a preliminary attempt to predict sham versus active TMS, which is a validity check that the prediction model is working as anticipated, as differentiating active from sham TMS should be relatively easy due to differences in the artifact and morphology of the iEEG waveform. As the predictive models were not very accurate, there were concerns about moving forward with the current models to more complex analyses. We had plans to progress these analyses further, using the fMRI time series data to predict the evoked responses, but never made it this far as the other members of the research team moved on to other projects.	

Brief summary of accomplished results:

We have developed and validated a Random Forest model to accurately predict Sham/Active transcranial magnetic stimulation (TMS) using extracted features (amplitude, variance, and Z-score) in four regions (left and right anterior and posterior insula). The prediction accuracy is 0.73 for left anterior insula, 0.74 for right anterior insula, 0.64 for left posterior insula and 0.60 for right posterior insula.

Research report:

Aims (provided by PI):

The primary goal of this project is to use rs-fcMRI, DTI, and iEEG recordings of epilepsy patients to predict evoked potential spatial patterns following pulses of TMS.

Primary aim changed to test the effect of TMS-elicited evoked potential (EP) amplitudes on a single-trial level for particular brain regions, primarily to determine the accuracy for distinguishing between active and sham TMS.

Data:

Experiments were conducted on inpatients in the epilepsy monitoring unit currently undergoing iEEG monitoring with 100-200 intracranial electrode contacts for a period of 1-2 weeks. Patients undergo baseline rs-fcMRI, DTI, and iEEG recordings to establish baseline connectivity metrics, followed by a period of provocations including TMS and intracranial electrical stimulation during which intracranial recording captures downstream evoked potentials.

We tested the effect of TMS on single-trial EP amplitudes within particular brain regions to attempt to distinguish between active and sham TMS. If single-trial EP amplitudes better distinguish active from sham TMS pulses, this can provide some evidence to suggest that the predictive model can accurately use amplitude and waveform variability data to label trial conditions, which would be a first step towards trying to create predictive models for how TMS pulses propagate to regions of interest (ROIs) in the brain. The ROIs here were the anterior and posterior insula (InsA, InsP), which are regions expected to show active but not sham evoked potentials. We extracted 12 features in four regions of interest (left and right anterior and posterior insula). The parameters of TMS-elicited evoked potentials (EP) amplitudes included the variance, absolute amplitudes, and z-scores of EP amplitudes both ipsilateral and contralateral to the left DLPFC where TMS was administered. Each parameter was extracted in different time windows (P1(25-100ms), P2(101-200ms), P3(201-300ms), Pw(30-300ms)).

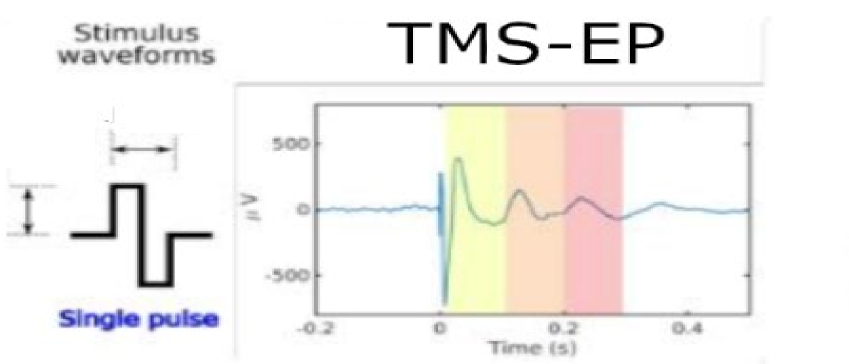

Figure 1. Example of EP amplitudes and its different time windows (P1: yellow; P2: orange; P3: red)

AI/ML Approach:

In this study, a supervised machine learning algorithm was implemented for prediction using Python. As many extracted features may be noisy, or highly correlated with each other, Random Forest (RF) algorithm was selected to predict sham/active group and performance assessed using 5-fold-cross-validation (Figure 1). Accuracy and F1-score were calculated to compare performance of different regions.

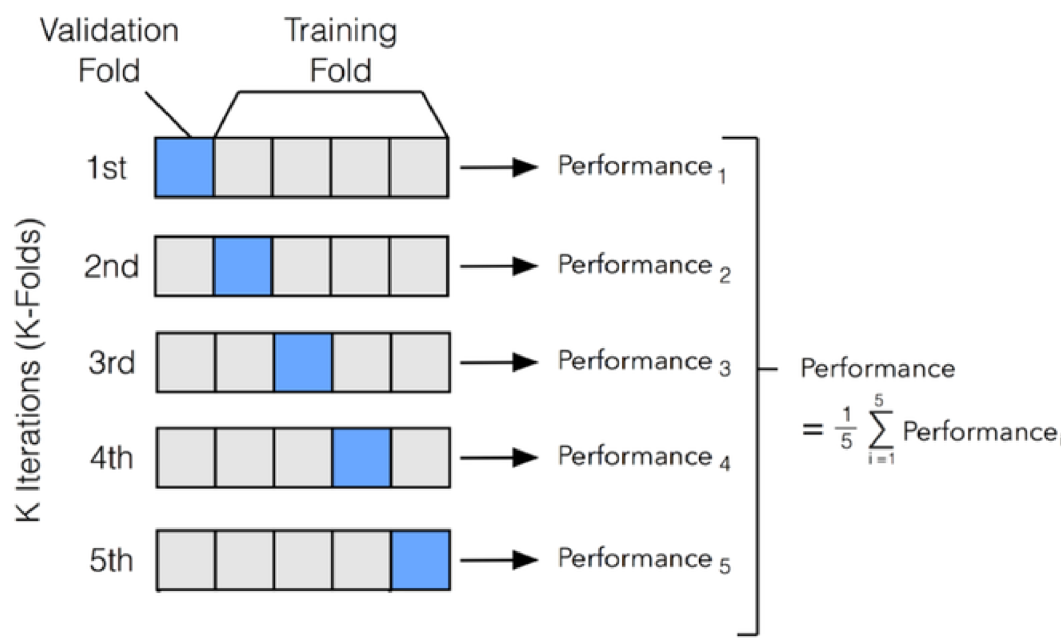

Figure 1. Representation of 5-fold cross-validation technique

Results:

One of the objectives of this research was to establish the relative importance of predictor variables/features in predicting sham/active. Feature importance is a technique that assigns a score to input features based on how important they are at predicting a target variable. For each region, feature importance is plotted in Figure 2.

Table 1 provides the model's predictive performance expressed in terms of respective confusion matrices for each region which were obtained using the K-fold cross-validation (with k=5) method. The confusion matrices given in Table 1 show the discrepancy between the predicted and actual observations for sham/active classes in the dataset.

Figure 2: Feature importance of variance, amplitude, and z-score in four different time windows in all four regions

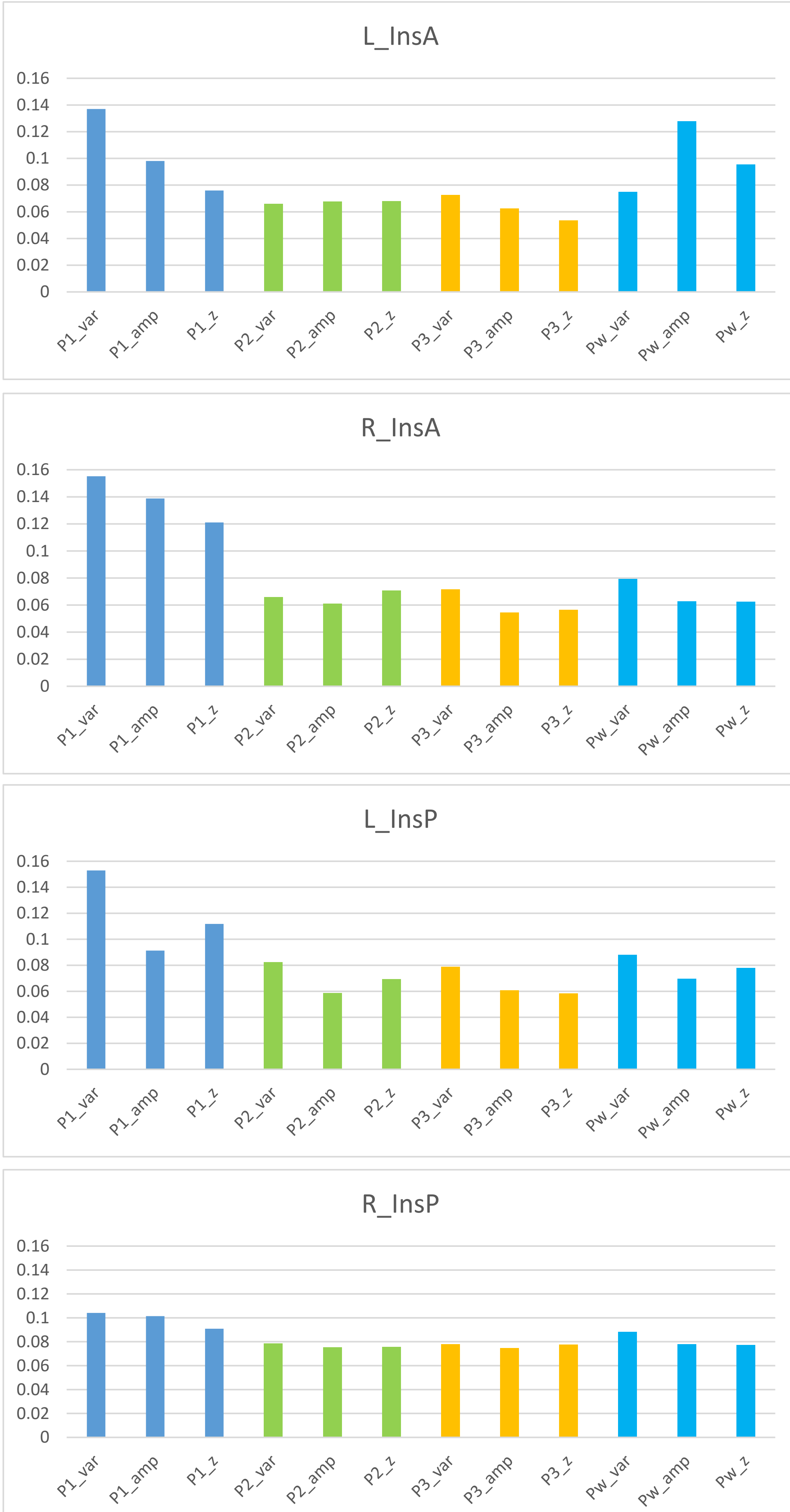

Table 1: Confusion matrix for the four regions

	Predicted	
Left InsA	Sham	Active
Sham TMS	404	169
Active TMS	143	419
Right InsA		
Sham TMS	337	85
Active TMS	114	239
Left InsP		
Sham TMS	811	385
Active TMS	442	647
Right InsP		
Sham TMS	615	264
Active TMS	417	391