Predicting Skill-Based Task Performance and Learning with fMRI Motor and Subcortical Network Connectivity

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***Abstract*— Procedural learning is the process of skill acquisition that is regulated by the basal ganglia, and this learning becomes automated over time through cortico-striatal and cortico-cortical connectivity. In the current study, we use a common machine learning regression technique to investigate how fMRI network connectivity in the subcortical and motor networks are able to predict initial performance and training-induced improvement in a skill-based cognitive training game, Space Fortress, and how these predictions interact with the strategy the trainees were given during training. To explore the reliability and validity of our findings, we use a range of regression lambda values, sizes of model complexity, and connectivity measurements.**

Keywords—procedural learning; ridge regression, basal ganglia, motor control, skill, cognitive training

I. Introduction

Cognitive training aims to improve cognitive functioning in healthy and clinical populations through training-induced changes in brain connectivity [1,2]. In order to understand how to improve cognitive function, it is important to investigate what differs in the brain of high and low performing individuals. Cognitive training paradigms typically involve use of skill based tasks that utilize targeted cognitive domains in additional to sets of constrained motor responses. The neural underpinnings of these cognitive training paradigms therefore involve the use of brain networks related to skill learning. To investigate the complex reorganization of computations that the brain undergoes over the course of cognitive training, we analyze performance on the cognitive training task as a measure of training-induced procedural learning. Procedural learning occurs through the search for optimal procedures, and new procedures are developed and refined based on feedback received [3], primarily through subcortical nuclei such as the basal ganglia.

The basal ganglia are the set of subcortical regions that are thought to be the hub of procedural learning, and changes in activation and connectivity in these regions are critical for skill learning [4]. Procedural learning of motor skills involves initial unitization of the skill by the striatum, followed by increasing striatal-motor connectivity as the skill is acquired, until finally the skill becomes automated and depends more on cortical interconnectivity [5]. The brain regions associated with procedural skills have been defined, however there exists little understanding of whether individual differences in the neural correlates of initial procedural skill performance and procedural learning are associated with these networks as well. Cognitive functioning occurs through processing of distributed sets of regions in the brain, and functional connectivity is a method for measuring how these distributed sets of regions are interrelated to one another in activity patterns [6, 7]. Characterizing how individual differences in skill relate to functional MRI network architecture may offer greater understanding of learning. In the current work, we test the hypothesis that subcortical and motor network connectivity predicts initial performance on a skill-based cognitive training task, as well as learning rate in this task. Furthermore, in aim of assessing the reliability of our solutions, we assess these questions through a wide variety of model parameters and sizes.

II. Methods

A. Participants

The current study used young adult participants' MRI scans collected from two separate Space Fortress training studies that followed similar neuroimaging and training protocols and have been individually described elsewhere [8, 9]. All of the final 68 subjects trained with Space fortress, a complex, multi-modal videogame that was developed by cognitive psychologists as a tool to study how different training strategies affected learning [10], and subjects were scanned in the MRI while playing Space Fortress before and after training. Briefly, this game requires extensive use of motor control, executive control, working memory, and stimulus-response learning. While players use a joystick to fly a ship and destroy the Space Fortress, they must simultaneously monitor their resources, look out for foes and friends, monitor streams of symbols off-screen, and fly their ship in a slow and controlled circle around the central Space Fortress. Trainees followed one of two training strategies, fixed priority (FP), or variable priority (VP). During the training, the FP group is encouraged to maximize their overall score. In contrast, trainees in the VP group have each training session split into several blocks, during which trainees are instructed to maximize their score on each of the game subtasks. Participants must perform the task as an intact whole, but during each block they focus their attention on maximizing performance on a single subtask. For example, participants would focus on controlling the ship's movement pattern while handling other game elements only in their spare capacity [11].

B. RCI Calculation

To reliably estimate the improvement of our trainees in Space Fortress, we calculated their reliable change index (RCI) [11]. This metric allows investigators to examine longitudinal changes in performance while taking test-retest reliability of the metric into account [12, 13], and is essentially formulated as a Z-scored pre-post difference score. We also calculated an RCI-residual by regressing the pre score on the RCI score. Creating an RCI-residual score allowed us to predict improvement in Space Fortress independent of pre score differences.

C. MRI Acquisition

We acquired functional MRI as the subjects played Space Fortress, and collected structural MR images as well. The structural MPRAGE images were skull stripped, and these images were linearly registered to the MNI 2mm brain template with 12 degrees of freedom. Each subject's functional MRI images were motion corrected, and linearly registered to the corresponding structural image with 6 degrees of freedom. These registration transformations were combined to register the functional data to the MNI template. All registrations were performed with FMRIB's FSL program [15]. During our functional acquisitions, participants played Space Fortress in the MRI scanner with the same type of joystick they trained with. For functional connectivity network analysis, we chose the nodes for the subcortical and motor networks from the Petersen 264 node network atlas [16]. To extract and process the network connectivity information, we calculated averaged timecourses for each node within each subject's motor and subcortical networks. Previous literature has suggested that correlation and partial correlation represent different aspects of network construction [17-19]. Therefore, we used both Pearson's correlation and partial correlation to assess the relationships between these time courses. We used these correlation values as features in separate predictions, and present and discuss implications of both sets of results.

D. Machine Learning Predictions

To train and test our ridge regression algorithm, we used leave-one-subject-out (LOSO) cross validation. Within each cross validation loop, we ranked all features in the training group by absolute correlation strength [20]. We created feature sets of the top 1 to the total set of features, and predicted each left out subject using these feature sets. After running through all n cross validation folds, we correlated the vector of predicted behavioral scores for all subjects with the vector of actual behavioral scores. In order to assess the bias in our models and significance of our predictions we created a distribution of null model simulations. To create these null models, we randomized behavioral scores and performed the procedure outlined above to predict the randomized values. We repeated this procedure 20 times to create a distribution of null model performance. To assess model significance, at each point we computed number of standard deviations above the null model that our model performed, and applied a Holm-Bonferroni correction for multiple comparisons. Model correlation values that were 3.60 and 4.03 standard deviations above the mean of the null distribution were deemed significant ($p < 0.05$) for the subcortical and motor network respectively. To assess the reliability of our feature set in predicting improvements in SF, we evaluated the performance of our model across a range of model sizes and lambda values. Since the lambda value used can have a significant impact on the performance of the regression, rather than using nested cross validation to search for the lambda values that optimize the performance of the model, we were interested in assessing the interaction of model size and lambda values in our sample. We ran our data with a range of lambda and assess how these parameters changed model performance.

III. RESULTS

We separately used the motor network and subcortical network to make predictions in order to assess whether a given network would be predictive for initial performance in Space Fortress versus RCI score. Connectivity in the subcortical network demonstrated above chance predictive accuracy initial Space Fortress performance for a range of model sizes and lambda regularization suggestive of the role of this network in initial task acquisition (Figure 1A: 22/315 models passed H-B correction). We find that only the VP groups' subcortical networks predict the RCI score in Space Fortress training (Figure 1B: 0/315 models passed H-B correction; 1C: 96/315). Furthermore, we find that when the initial score is regressed out of the improvement score, the FP group's subcortical network connectivity does not predict the improvement score well, while the VP group remains predictive (Figure 1D: 9/315; 1E: 32/315). These results support previous literature suggesting that individual differences in subcortical regions, such as the caudate, predict learning in the variable priority strategy uniquely, and not the fixed priority strategy [20]. Furthermore, we find that these predictive accuracies are stable across a range of lambda values and model complexity, suggesting that this relationship does not differ drastically between minor variations in the model. Finally, we see relatively little interaction in the size of the model and the regularization value across all calculations.

We find that motor connectivity predicts initial performance for a wider range of models compared to RCI (Figure 2A: 388/1827 total models passed H-B correction; 2B: 19/1827; 2C 100/1827); however, when comparing the subcortical and motor predictions across the lower end of model complexity range (0-70), we see that the motor network is significantly less predictive of initial task performance than the subcortical network. Interestingly, the motor network VP predictions demonstrate higher predictive accuracy in the improvement scores but not improvement scores with pre score regressed out. This may be reflective of the motor connectivity predictions in the VP condition being more highly dependent on the initial performance score, rather than learning score.

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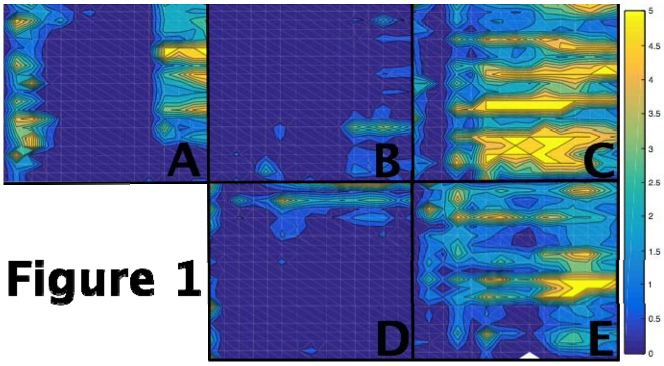


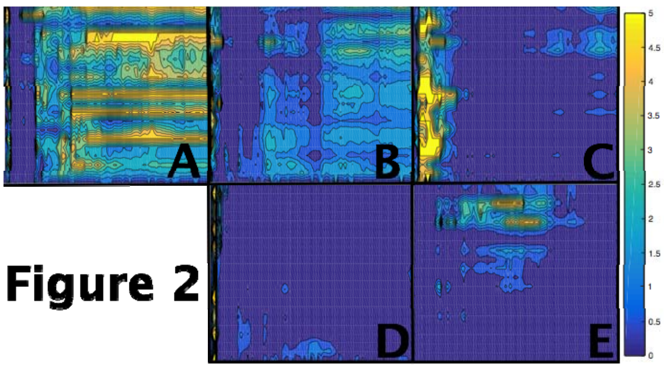
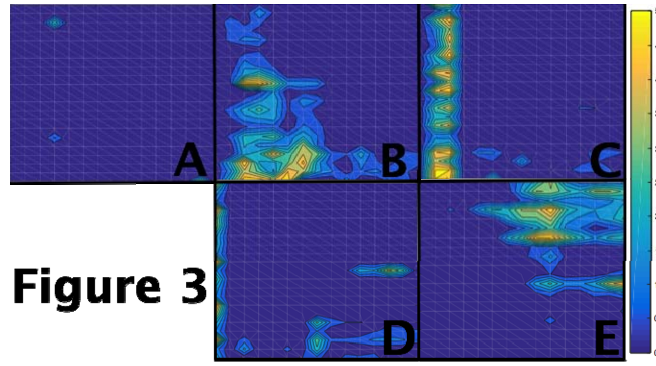


Figure 1 & 2: All plots display lambda values on the Y axis from 0-10, and number of features used in each model on the X axis from 0-78 for the subcortical network (Figure 1), and 0-435 for the motor network (Figure 2). These contour plots display the difference in predictive accuracy of our experimental model compared to the 20 simulations at each point. The right hand color bar represents how many standard deviations above the mean our model performed higher than the simulation values, from 0-5 standard deviations. A) Network predicting initial performance; B-C) Network predicting score improvements in the FP and VP group respectively. D-E) Network predicting score improvements with initial performance regressed out.

We repeated these analyses using a partial correlation association metric to assess whether our results would replicate across network estimation techniques. The partial correlation results show that the subcortical network connectivity is not predictive of initial performance (Figure 3A: 0/315), but it is moderately predictive of learning in both FP and VP groups (Figure 3B: 14/315; 3C: 19/315). Both 1E and 3E indicate that for the VP group, subcortical network connectivity is predictive of improvements in Space Fortress. Furthermore, the partial correlation motor network results in Figure 4 largely replicate the correlation motor network results in Figure 2. We find that partial correlation network is highly predictive of initial task performance (Figure 4A: 573/1827), and the VP group's connectivity is more predictive of RCI than the FP group, although both are predictive (Figure 4B: 39/315; 4C: 226/315). The drop in predictive significance between the RCI predictions and the RCI residual predictions demonstrate that these partial correlation predictions may be equally dependent on the shared variance between the RCI and pre-training performance scores.



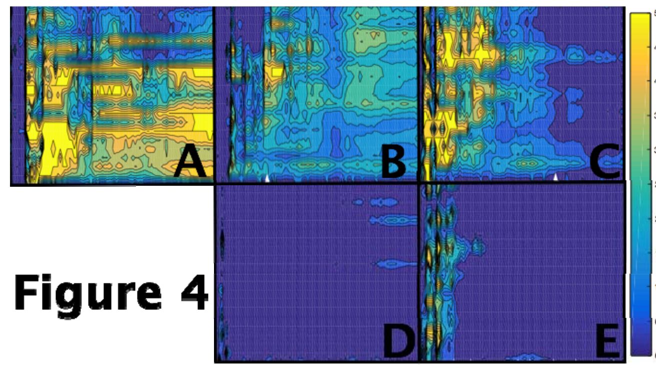


Figure 3 & 4: These predictions used partial correlation based edge strengths as features rather than Pearson's correlation. Figure 3 and 4 are partial correlation versions of Figure 1 and 2 respectively.

IV. Discussion

The basal ganglia is especially important for initial task acquisition [5]. While trainees had brief exposure to Space Fortress before going into the MRI scanner, all trainees would be considered still in the initial acquisition phase of skill learning based on their position on a logarithmic learning curve [20]. Therefore, our findings extend previous work by demonstrating that on-line subcortical and motor connectivity during initial task exposure is related to initial performance in skilled tasks. Initial task acquisition is determined in part by the subcortical structures, and the involvement of motor structures plays a role at initial exposure, but motor connectivity is less effective at predicting initial performance compared to the subcortical network for the possible range of models from 0-70 features. These findings support the notion that subcortical connectivity would be particularly sensitive to initial task acquisition.

Current results also demonstrate interesting dissociations between the two training strategies. We find that both FP and VP groups score improvement is predicted by subcortical connectivity (Figure 1B-C), yet score improvement residuals are much less predictable for the FP group (Figure 1D-E). This finding suggests that the connectivity of the subcortical network is more important for the entirety of the learning process in the VP compared to FP group. This is supported by previous work suggesting that the FP strategy is a procedural learning based strategy. As such, FP processing of the Space Fortress task would more quickly transition from subcortical based processing to cortical processing [11]. In contrast, in the

VP condition subjects' are constantly challenged to play the game in different ways, preventing the restricted and repetitive learning environment typical in procedural learning. This suggests that for the VP group, patterns of subcortical connectivity would have an impact not only on initial task acquisition, but also score improvement as measured by RCI and RCI residuals. We find evidence for this in our correlation network analysis, and replicate this finding in our partial correlation network predictions as well.. These findings motivate further work into how individual differences in network conenctivity contribute to propensity for quicker initial task acquisition and steeper learning curves.

An important aspect of the current results regard replicability of predictions with correlation and partial correlation results. We find that partial correlation shows predictive accuracy compared to correlation for the motor network predictions of initial performance. Given that partial correlation networks are thought to reflect underlying anatomical connectivity more accurately than correlation networks, this result may suggest that anatomical rather than functional characteristics of the motor network are more predictive of initial task performance.

The current work faces some limitations that will be overcome through future work in this domain. For example, we plan to apply nonlinear MRI registration methods for better subcortical network alignment. Another important area of investigation involves more detailed comparison of predictions using partial correlation and correlation networks, as well as comparison of classic inner cross-validated grid search of lambda values and our current contour plots

V. CONCLUSION

We find support for the notion that subcortical and motor connectivity are related to initial task performance and learning in a complex multimodal cognitive training task. We find that training strategy dissociates the informativeness of these networks in predicting training-induced improvements in Space Fortress. These results motivate further work into how pre existing differences in network connectivity contribute to individual differences in performance and learning.

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