rsfMRI Brain Network Classification

Computer Integrated Surgery II

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Introduction

- Resting state functional magnetic resonance imaging (rsfMRI) offers an opportunity for improved pre-operative planning in brain surgery
- Only a handful of physicians in the country can currently classify rsfMRI brain networks at high resolutions
- Automating the classification of rsfMRI network components can provide valuable access to this emerging form of pre-operative care

The Problem

- Current pre-operative planning in brain surgery relies on sparse task-based fMRI readings to identify critical structures
- rsfMRI measures the functional organization of the brain at higher resolution; small and complex brain networks make rsfMRI more useful than task-based fMRI but are difficult to classify
- Classification of small and complex brain networks requires an understanding of the hierarchical relationships of these networks
- Classification is essential to defining the boundary regions of operation for a surgeon

The Solution

- The goal of this project was to design a classification algorithm that incorporates hierarchical relationships between brain networks

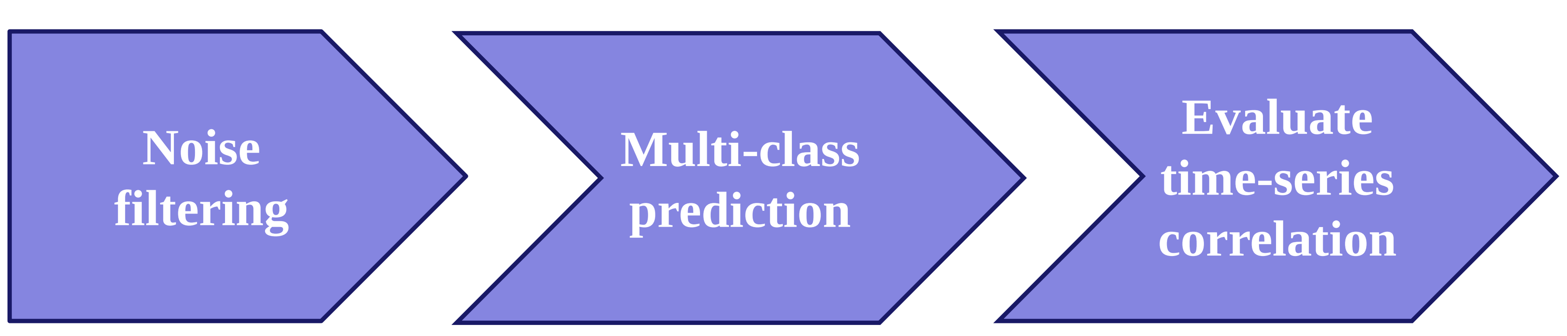

Figure 1: Standard labeling workflow

- **Noise Filtering:** A shallow convolutional neural network with custom architecture was implemented; initially trained on 20 subjects at 20 component level from Washington University School of Medicine 120 dataset labelled at Johns Hopkins University
- **Multi-class Prediction:** A shallow convolutional neural network with custom architecture was implemented that can handle variable output class ranges based on noise filtering and component granularity; network is optimized for 64x64x32 normalized cerebral scans; initially trained on group ICA of aforementioned Washington 120 dataset

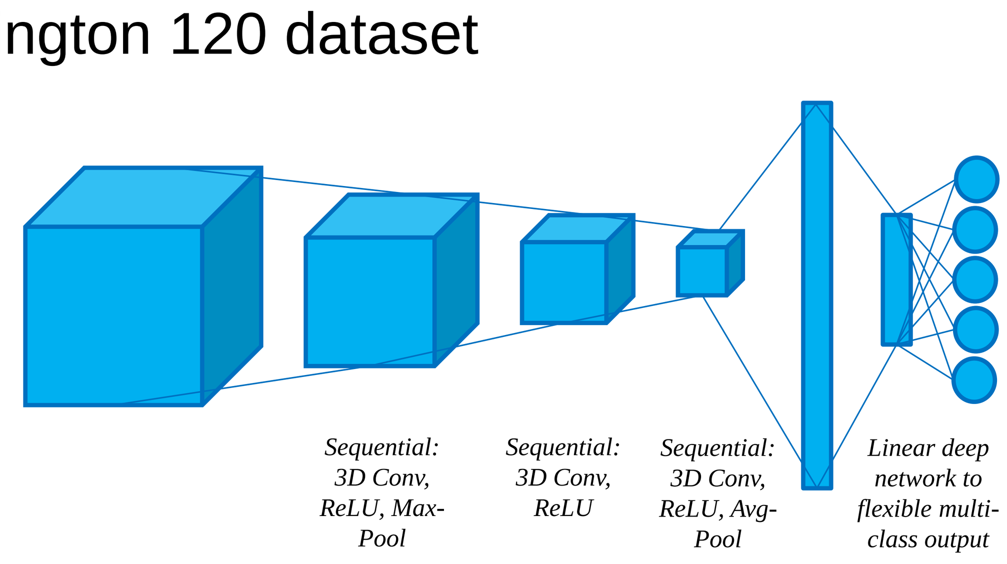

Figure 2: Custom Multi-class Network Architecture

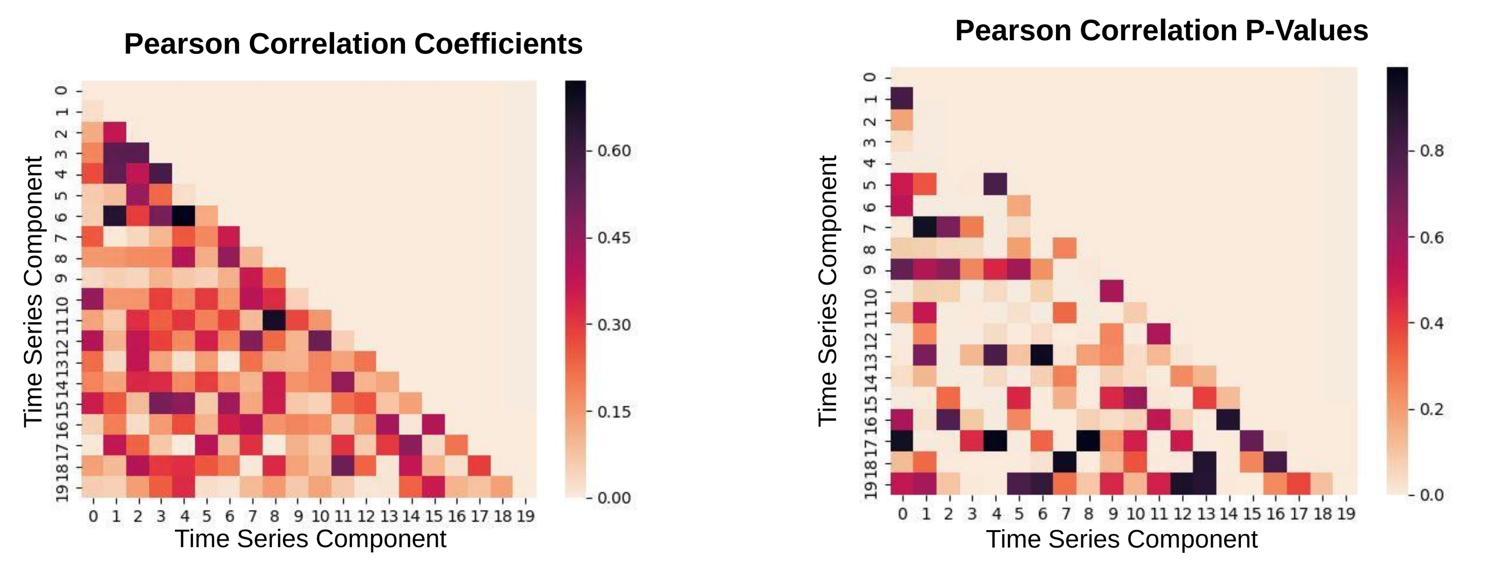

Figure 3: Hierarchical relationships between network components drawn from Pearson correlations between individuals' component time series

- **Time-series Correlation:** Hierarchical relationships between network components were evaluated when the multi-class predictor achieved low confidence; strongly correlated components indicate similar neuronal firing patterns; low confidence multi-class prediction and network correlation indicates unidentified brain network

Outcomes and Results

	Network	Noise
Network	74	5
Noise	2	19

Figure 4: Contingency table of noise classification in group rsfMRI study

	Precision	Recall	Accuracy
Attention	0.850	0.944	0.840
Language	1.000	1.000	1.000
Default Mode	1.000	1.000	1.000
Motor	1.000	0.952	0.960
Total	0.963	0.975	0.950

Figure 5: Performance statistics of noise classification in network separated testing

- Noise filtering is highly successful in preventing miss classification due to non-random noise signatures
- Clinical grade accuracy is achieved with shallow multi-class network
- Pearson correlation successfully picks up outliers

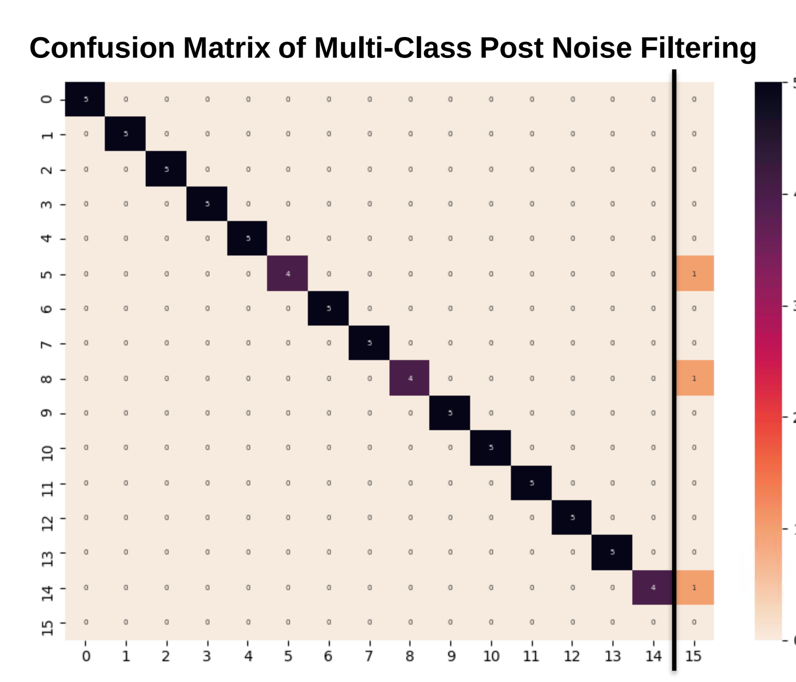

Figure 6: Confusion matrix of multi-class network assignment in group ICA study post noise filtering, with label 15 reserved for low confidence classifications

Lessons Learned

- Deeper and more advanced machine learning solutions do not always offer the best model
- Clinical applicability must always be kept in mind

Future Work

- Validation on cases of brain lesion
- Incorporate transferring learning on CNNs

References

- Shruti A, Sair H, Pillai J. Limitations of rsfMRI in the setting of focal brain lesions. Neuroimaging Clin N Am. 2017 Nov. 27(4); 645:661.
- Bailey P, Zaca D, Basha M, Agarwal S, Gujar S, Sair H, Eng J, Pillai J. Presurgical fMRI and DTI for the Prediction of Perioperative Motor and Language Deficits in Primary or Metastatic Brain Lesions. Journal of NeuroImaging. 2015 July 14.

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