Temporal and spectral characteristics of dynamic functional connectivity between resting-state networks

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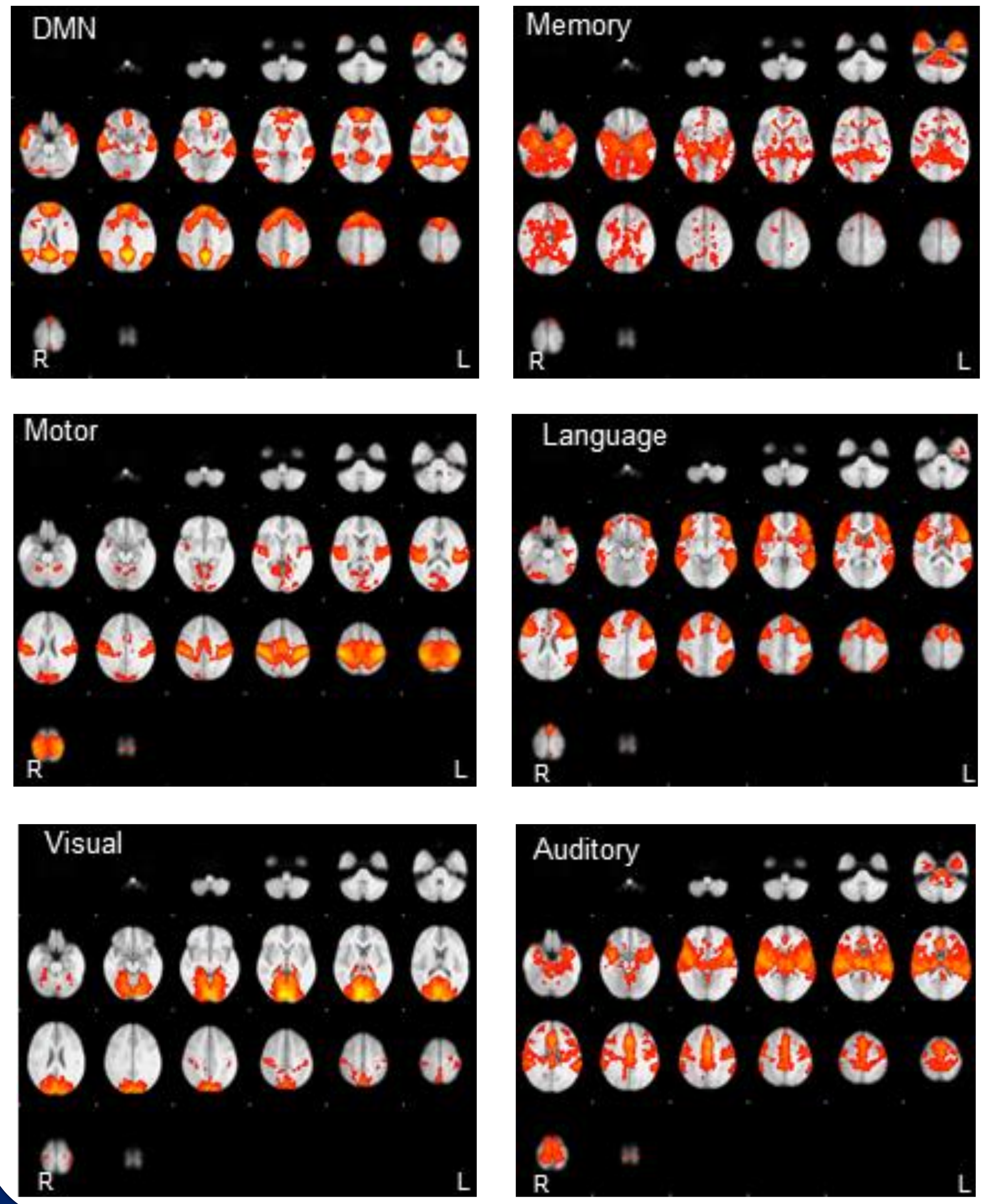
Motivation

- **Connectivity between DMN and other resting-state networks (RSNs)** plays a fundamental role in cognition in patients with epilepsy
- Majority of conclusions regarding connectivity between RSNs have relied on static connectivity
- Recent evidence suggests that functional connectivity is **dynamic over time**
- Objectives:
  - **Objective 1:** Evaluate **whether dynamic functional connectivity can improve prediction** for patients with temporal lobe epilepsy
  - **Objective 2:** Determine **which aspects of dynamic functional connectivity are most affected** in patients with temporal lobe epilepsy

Methods

Study sample
- 23 healthy controls (age, 31.1±6.5 SE; 8 females)
- 25 unilateral TLE patients (age, 33.6+7.8 SE; 12 females; epilepsy duration, 18.74+2.4 SE) from University of California Los Angeles Seizure Disorder Center
- Resting state fMRI (3T MRI, TR=2000ms, 300 volumes)

Resting state networks



Statistical modeling of dynamic functional connectivity (dFC)
- **Dynamic Conditional Correlation (DCC)**
  - Multivariate GARCH model
  - Correlations vary over time

Dynamic functional connectivity features
1. **Time domain features –** mean, variance, proportion of anticorrelated volumes, zero-crossing rate
2. **Frequency domain features** – properties of power spectrum

Classification of TLE v. healthy controls

Random Forests
- Sequence of decision trees applied to bootstrapped data
- Combine trees via majority vote for better predictions

Variable Importance
- Highlights importance of various dFC features for identifying patients with TLE

Key Results

Predictive accuracy for identifying patients with temporal lobe epilepsy

Classification based on 5 methods
- **GARCH-RF**, static correlation, mean and variance of dFC calculated based on sliding windows

Findings
- Proposed method obtains significant improvement in classification accuracy for **DMN-Memory** and **DMN-Visual** networks
- Resting-state networks involving the temporal lobe, such as the **memory** and **language networks**, achieve highest accuracy in discriminating TLE vs healthy controls.

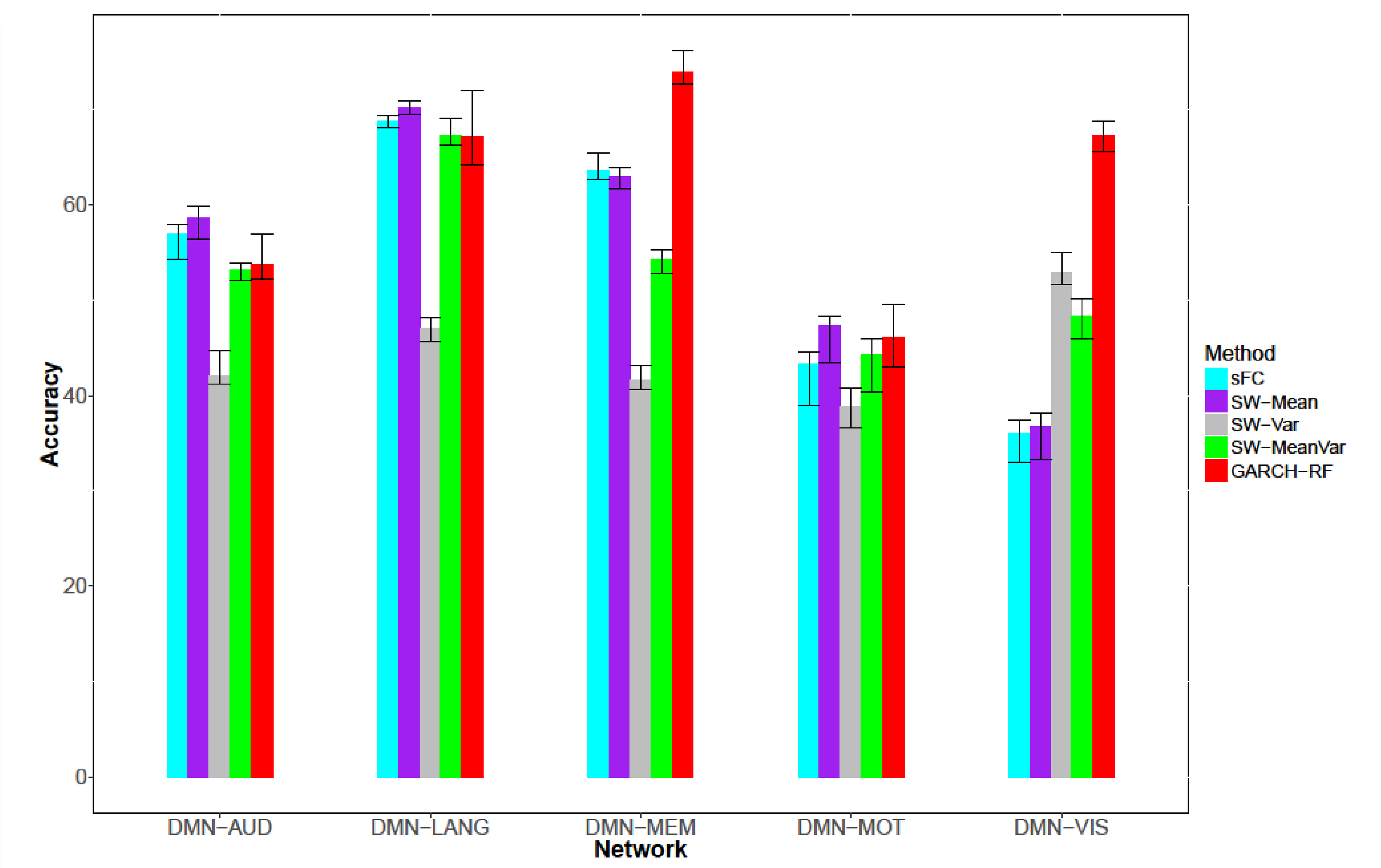


Figure 2. Predictive performance of dFC features. Classification accuracy (TLE vs. controls) based on connectivity between DMN and various resting-state networks is shown.

Feature classification importance

1. **Mean value and variance of dFC** capture a large amount of the signal which is useful in discriminating patient groups
2. Utilization of other dFC features **improves classification accuracy**
3. Features such as **ALFF-dFC** (amplitude of low frequency fluctuations in connectivity), **PAV** (proportion of anticorrelated volumes), and **PEAK** (spectral peak) may contain useful information not contained in static connectivity.

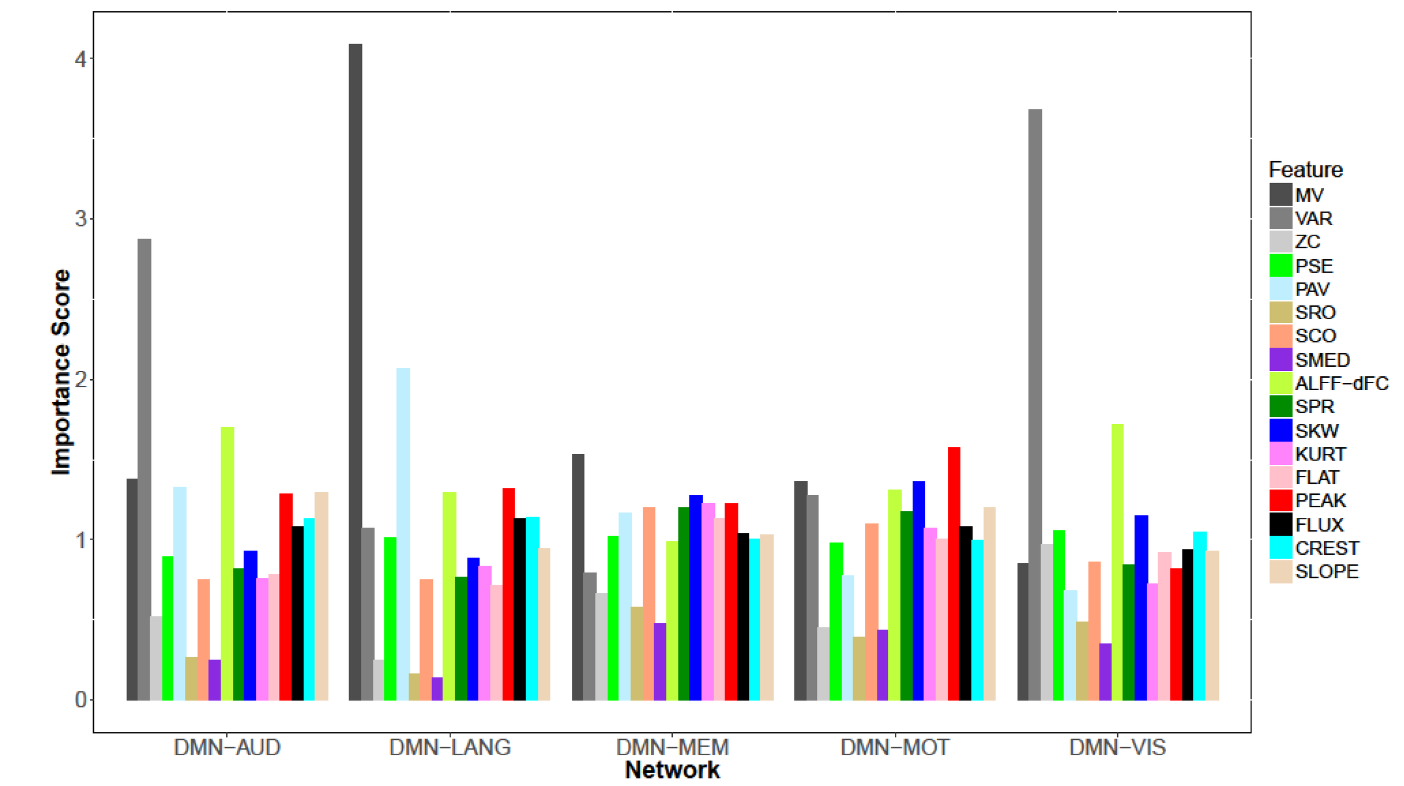


Figure 3. Variable importance scores of dFC features. Mean of Random Forest variable importance scores over ten replicates, for dFC features between DMN and various resting-state networks..

Conclusions

- **Wider consideration of the temporal and spectral characteristics of dynamic functional connectivity** may be useful for understanding which aspects of functional connectivity are altered in epilepsy
- **Superior predictive performance** is obtained using dynamic functional connectivity compared to traditional static measures

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