Graph Theory Complex Networks and Source/Sensor Analysis for (Real Time) Cognitive Workload Assessment

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Summary: We emphasized in the use of graph theory and complex networks models for brain connectivity analysis and we prioritized the small world model instead of random and hierarchical ones.

In a systematic approach we have analyzed off line and in real time the fatigue development and we have proposed biomarkers and source localization methodologies for best results.

We started using wet electrodes and wired EEG systems and in next round of experiments we used dry electrodes and wireless EEG systems to monitor, real time, biomarkers in smart phone.

Conclusions:: The prefrontal and frontal brain areas are mostly affected by fatigue and cognitive workload and biomarkers related with the sensors located close to these brain areas can be used for real time monitoring of the fatigue.

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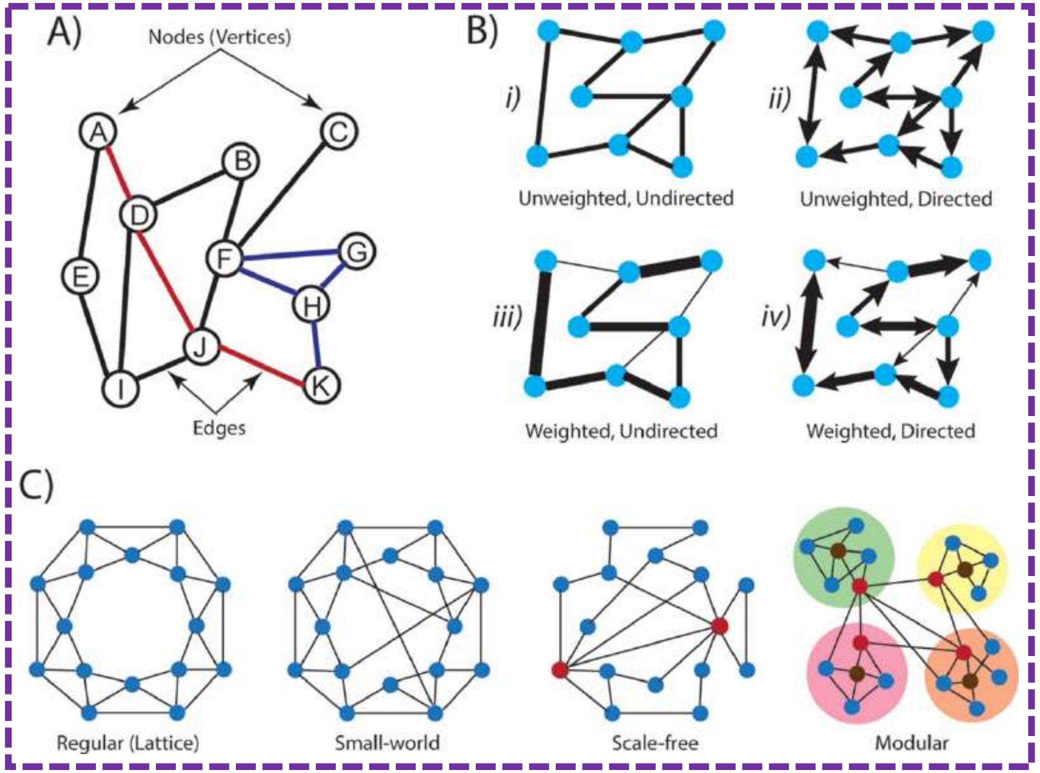
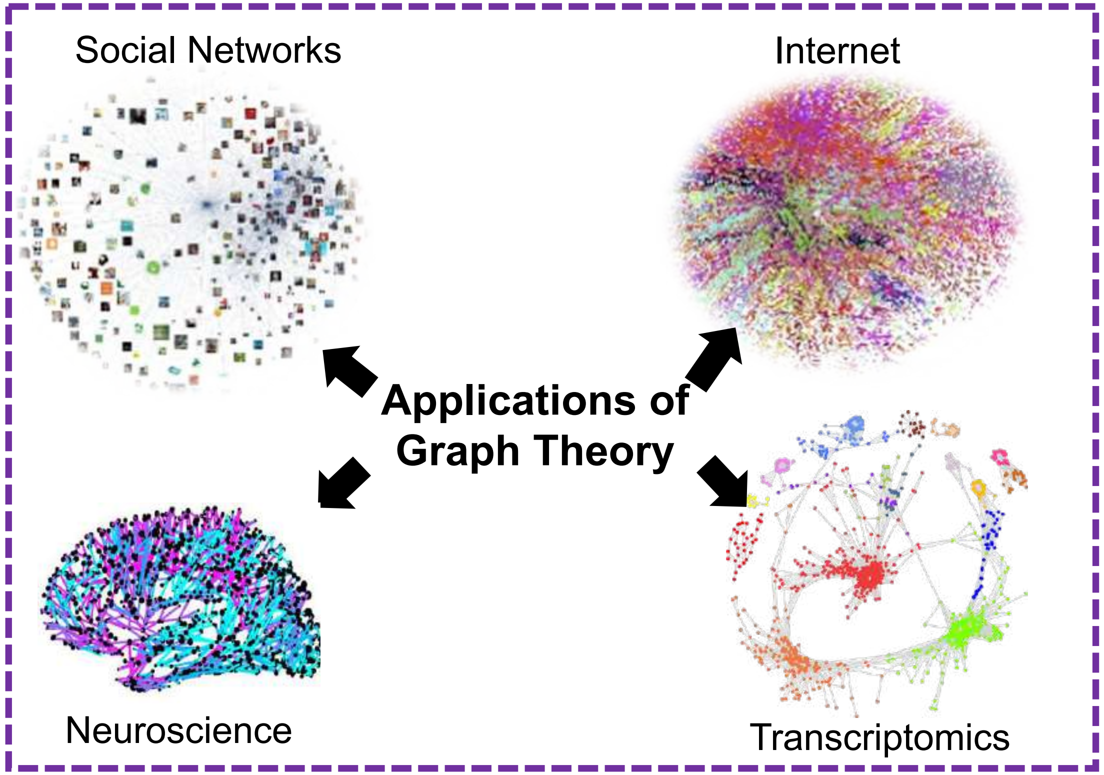
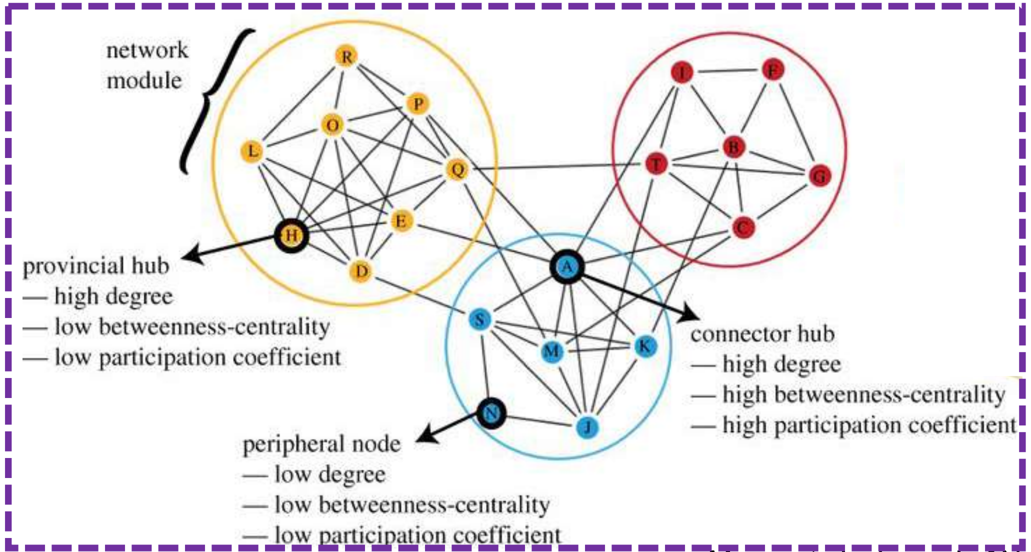
Introduction to Graph Theory



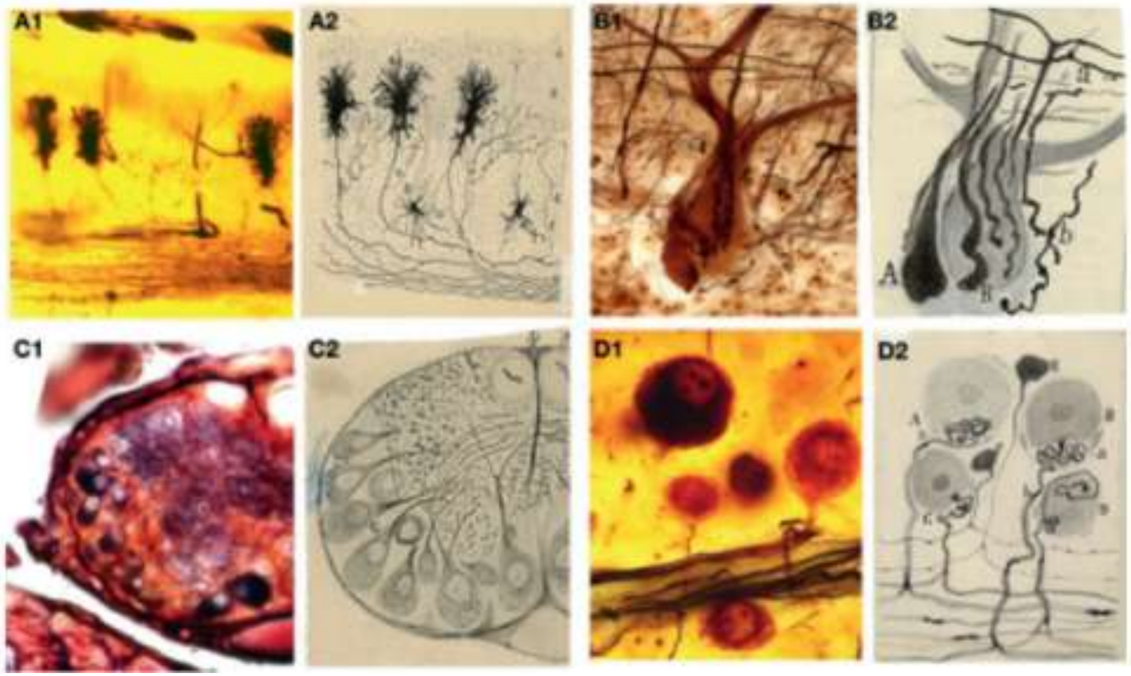


- Graph theory is a tool used to study complex networks (also known as Network Science), where the nodes represent distinct elements and the edges represent the connection between the elements
- Graphs can be weighted, unweighted, directed and undirected
- Graph theory has been widely applied in biological, social, telecommunication and computer networks
- Network analysis includes centrality measures, finding hubs, small worldness, motif analysis and community structures

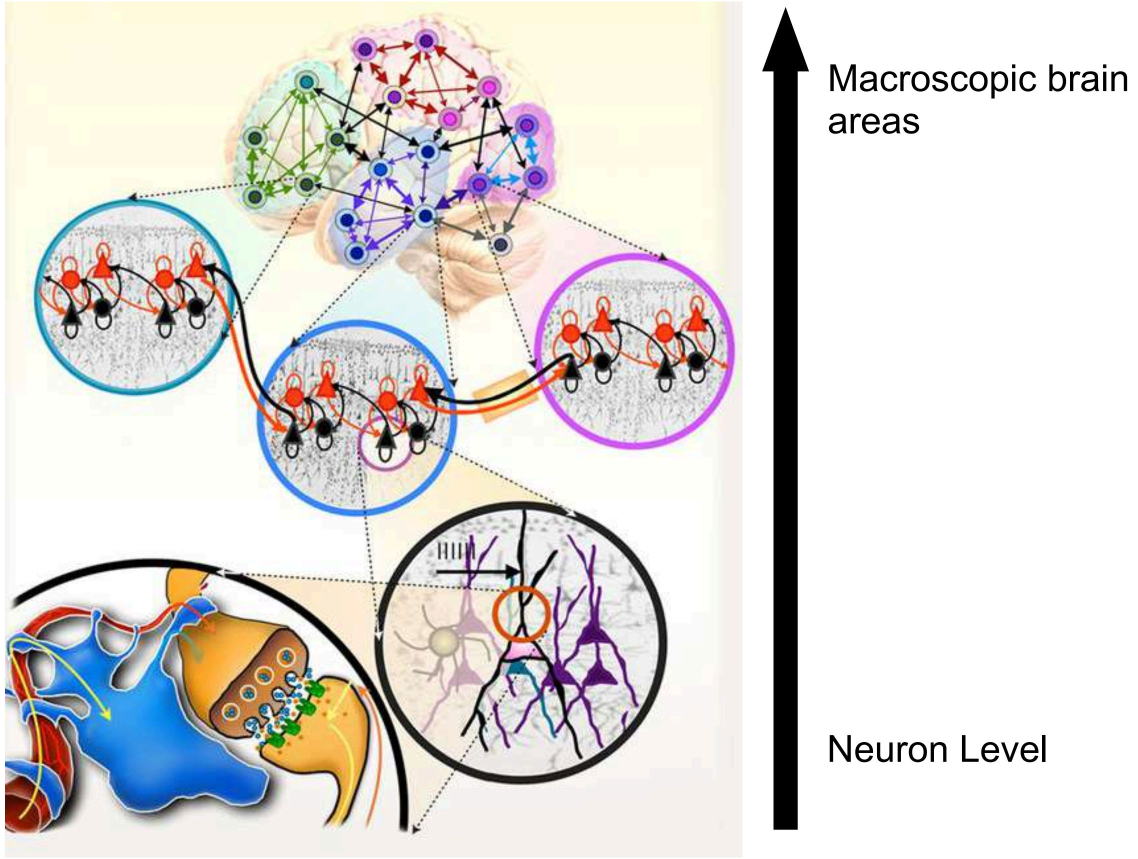


Mears et al., Journal of Neur., 2017
Lord et al., Royal Society, 2017

Introduction to Brain Networks



First microscopic study by Ramon that evolved neuron theory



Schematic representation of multiscale hierarchical organization in brain

- Seminal neuron theory, established by Ramon y Cajal's microscopic studies first showed the complex branching process in neurons and set the scene for graph theory analysis in neuroscience
- The microscale analysis was extended to the macroscopic level where the white matter connections and functional interactions were analyzed between the cortical brain regions
- Network theory provides techniques for analyzing these structural and functional interaction in the brain, along with their associated dynamics

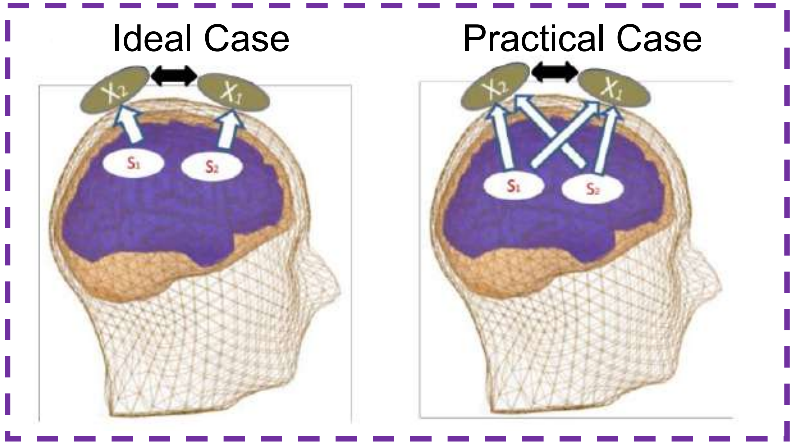
Fornito et al., Academic Press, 2016
Park et al., Science, 2013

Source Localization

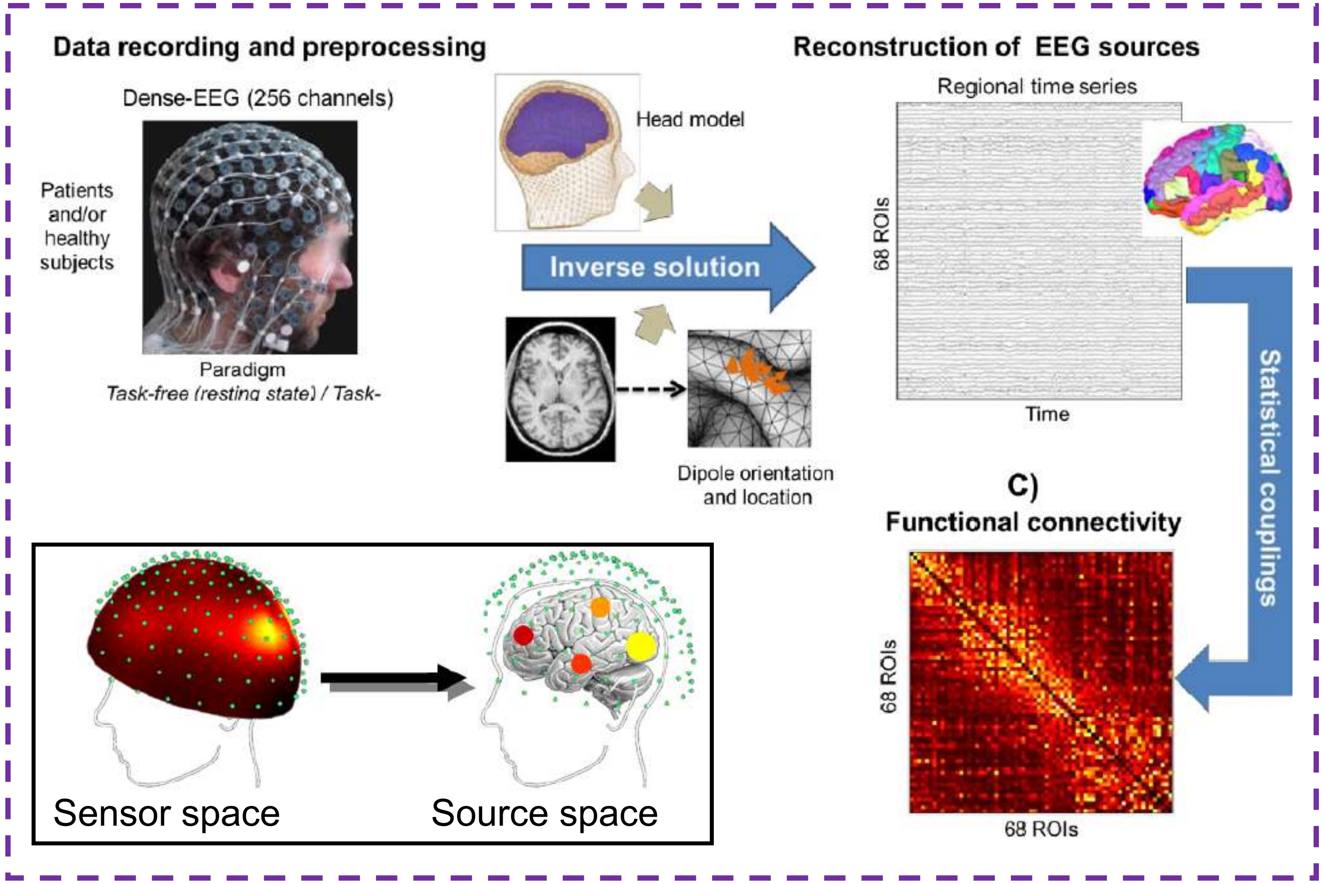
- Source localization provides brain functional connectivity at the cortical source level from the sensor level
- Provides higher spatial resolution to the EEG data and reduces the volume conduction effect
- Additional advantage from fMRI is the higher time resolution present in EEG

Data required for Source localization

- The scalp-recorded EEG signals
- 3-D position of the electrodes
- The head model, containing electrical and geometrical characteristics of the head
- The source model containing location and orientation of dipole sources



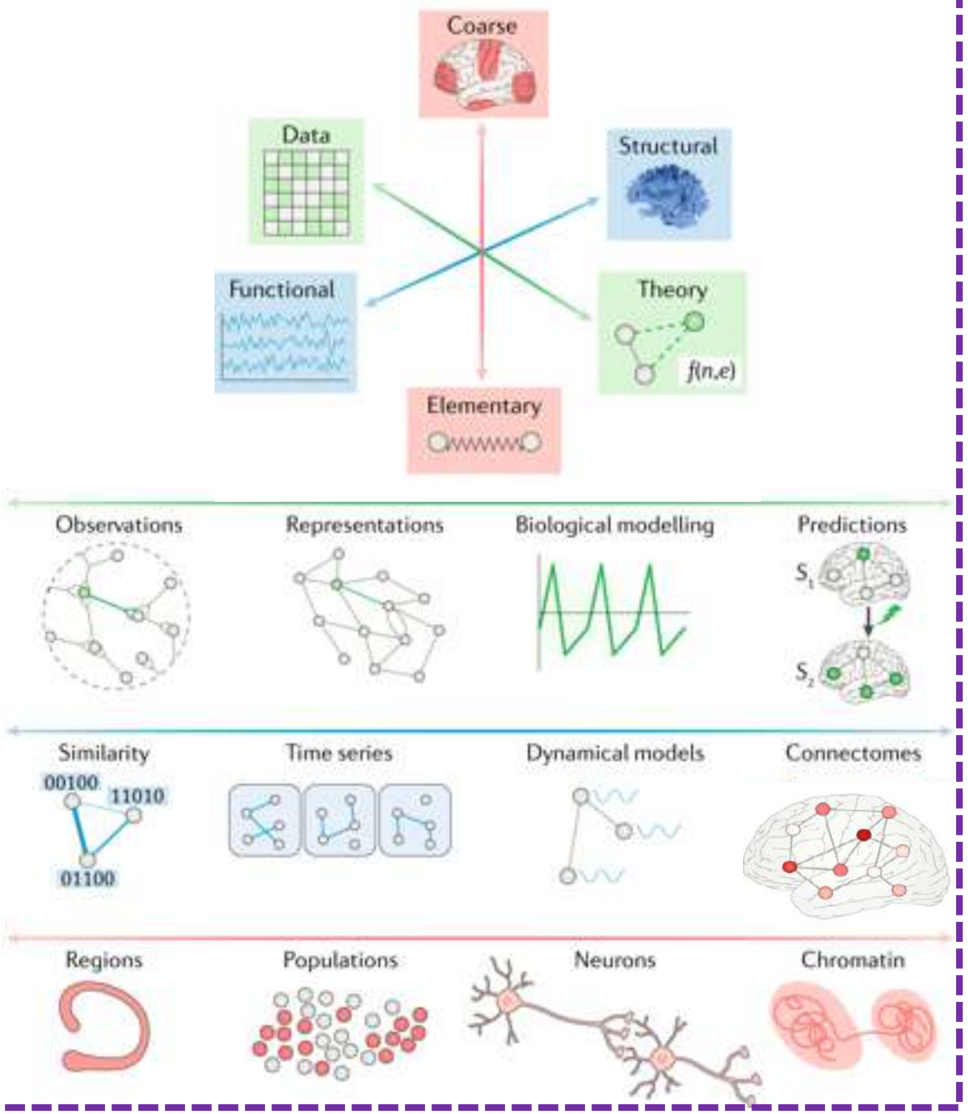
Volume conduction effect



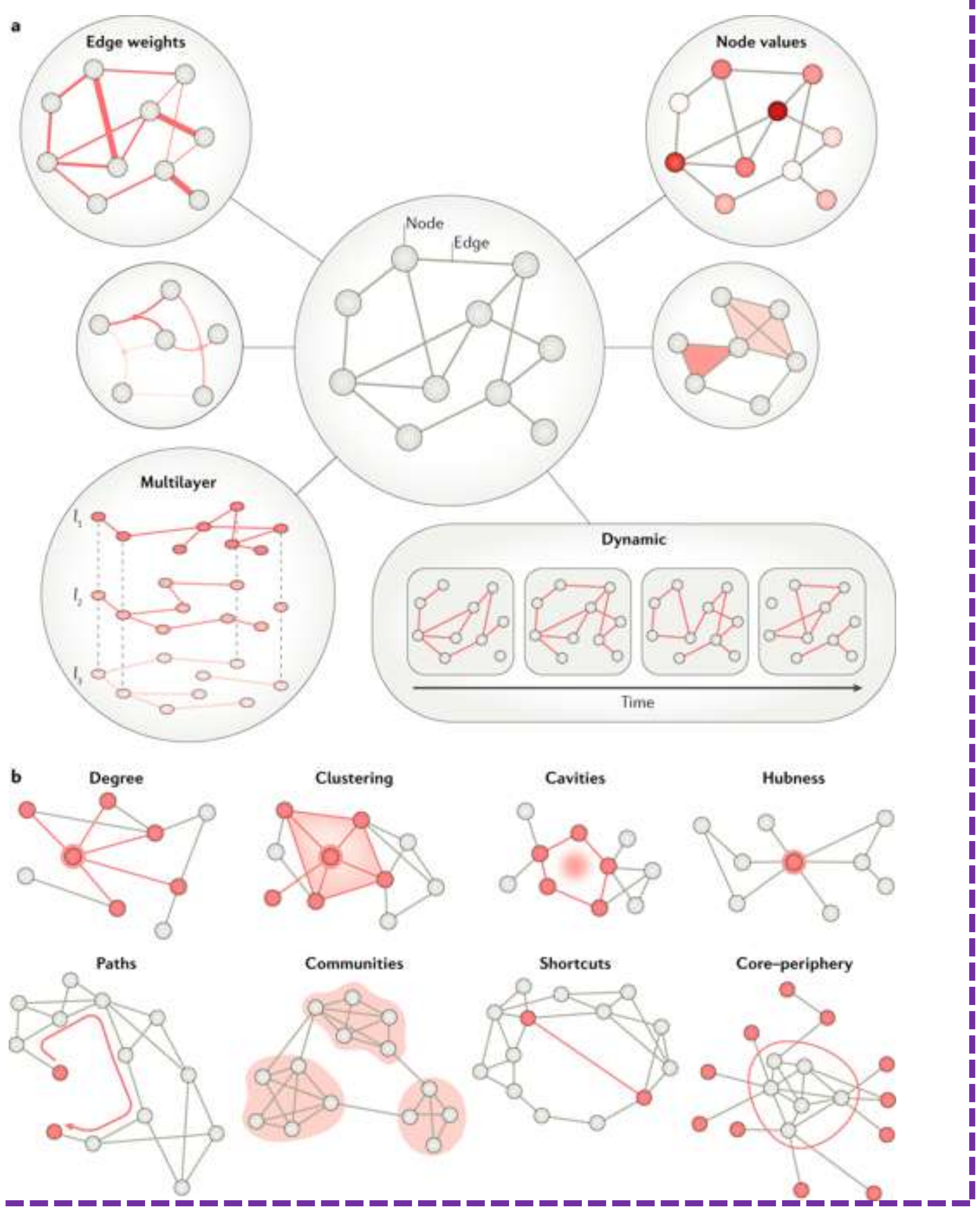
Steps involved in reconstruction of EEG sources from the sensor level

Hassan et al., IEEE Sig. Proc., 2018

Network Models used in Neuroscience



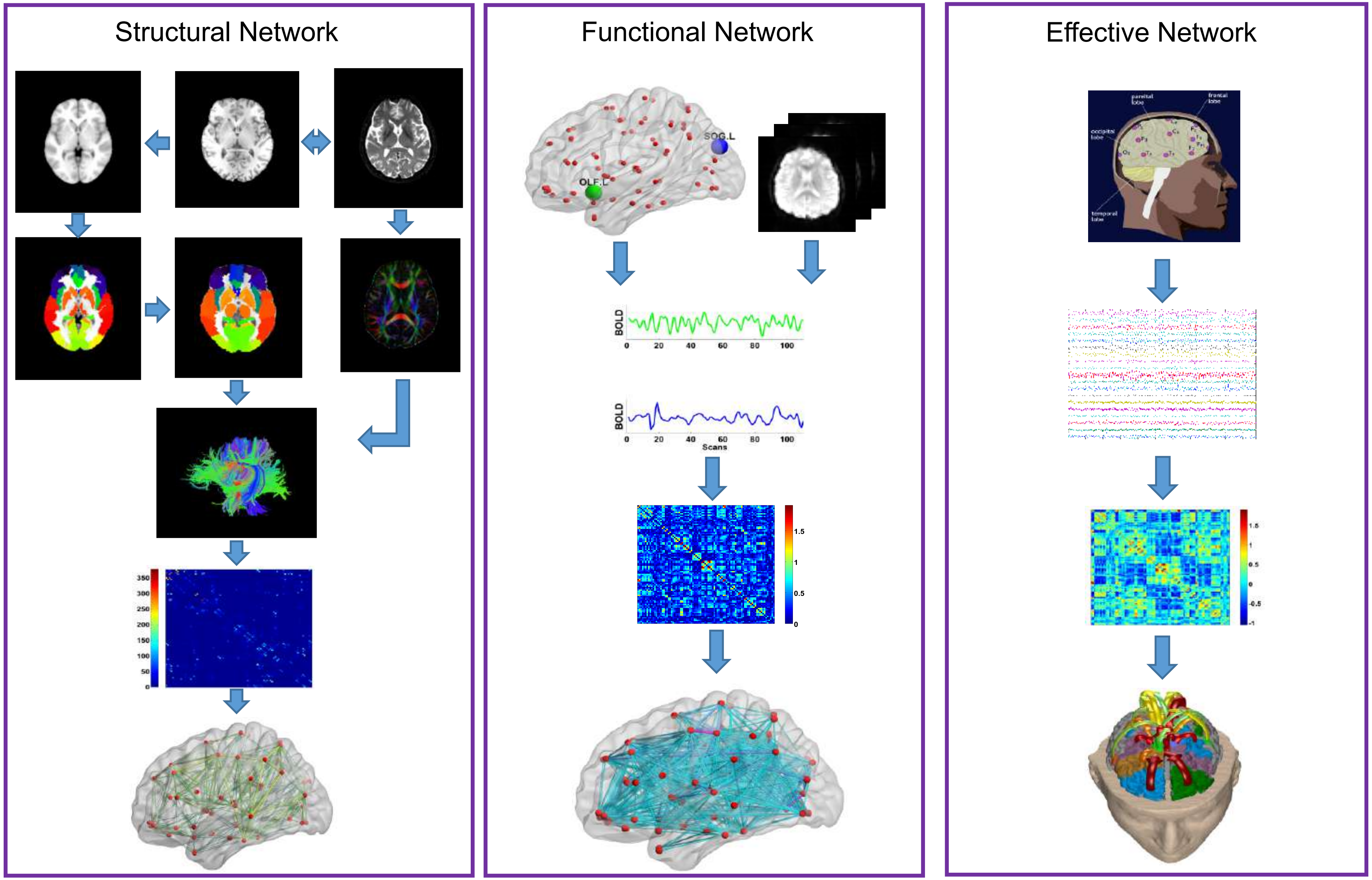
Different network model types



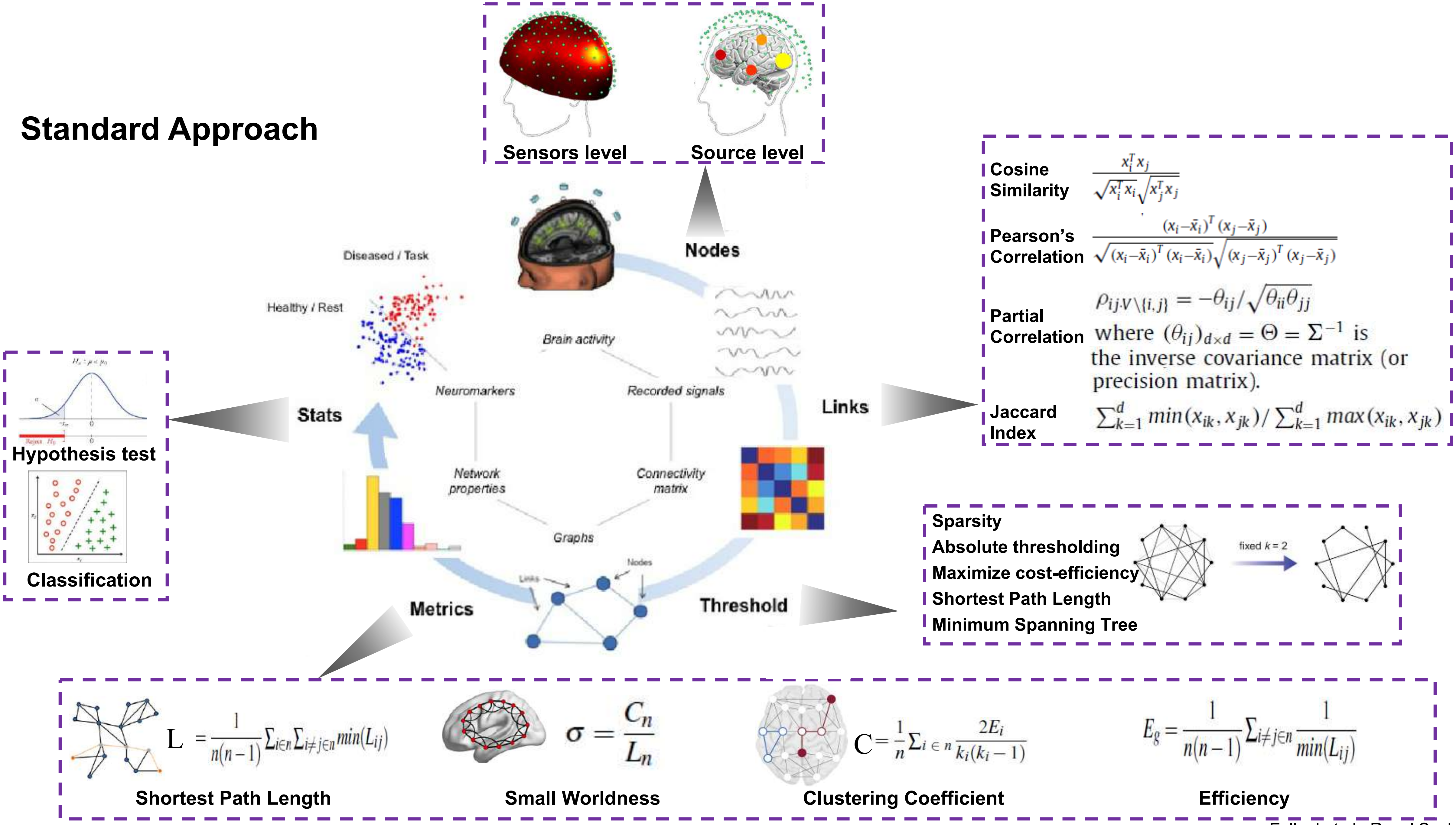
Schematic of network models used in neuroscience

Bassett et al., Nature, 2018

Types of Connectivity Network

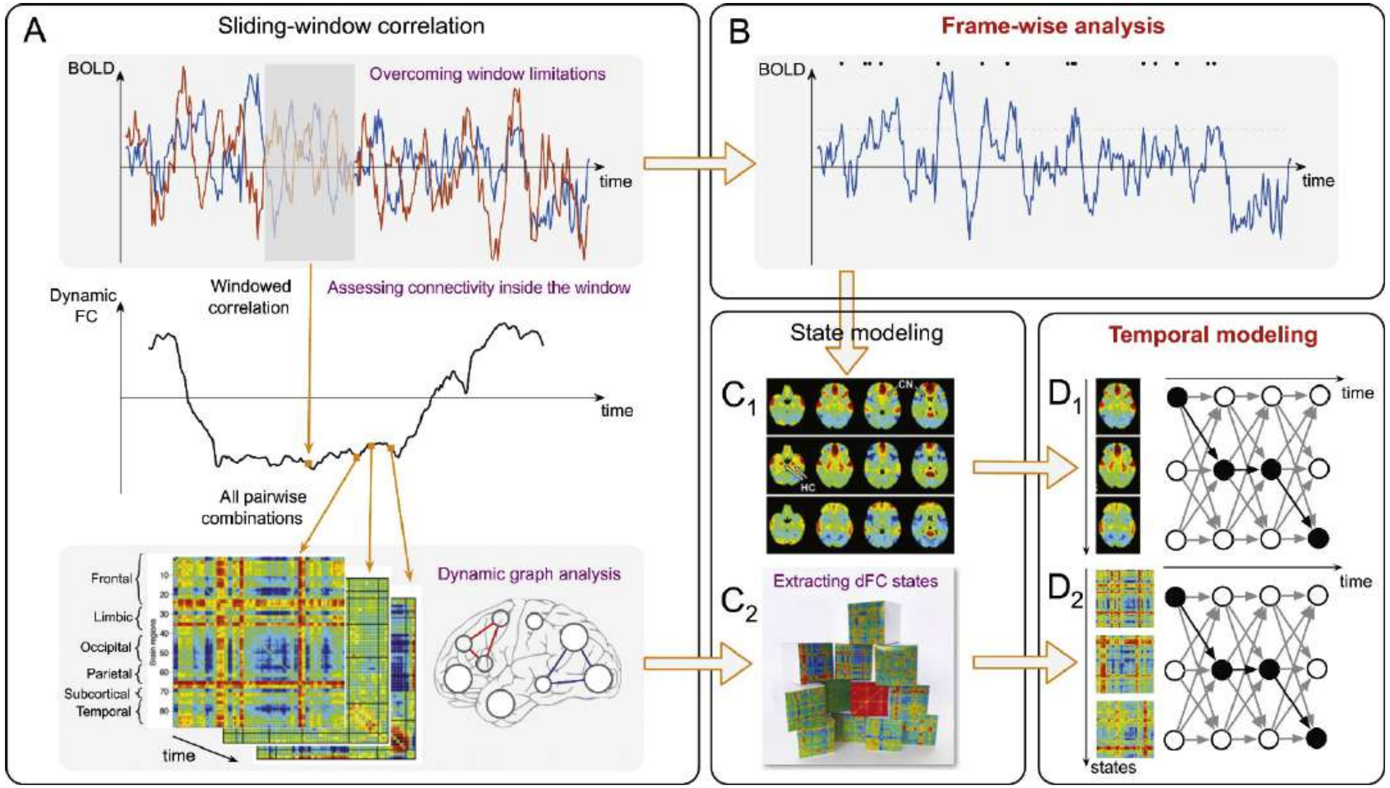


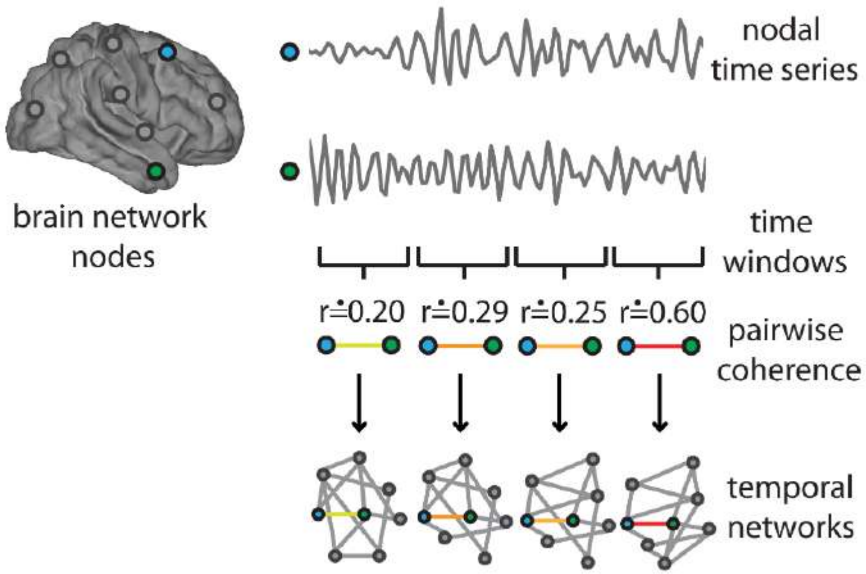
Standard Approach



Fallani et al., Royal Society, 2014
Qiao et al., Neuroimage, 2018

Dynamic Functional Connectivity





Current Challenges:

- Functional connections in human brain might **fluctuate over time,** which cannot be found from the standard approach that relies on a static graph to represent functional connectivity.

Solution:

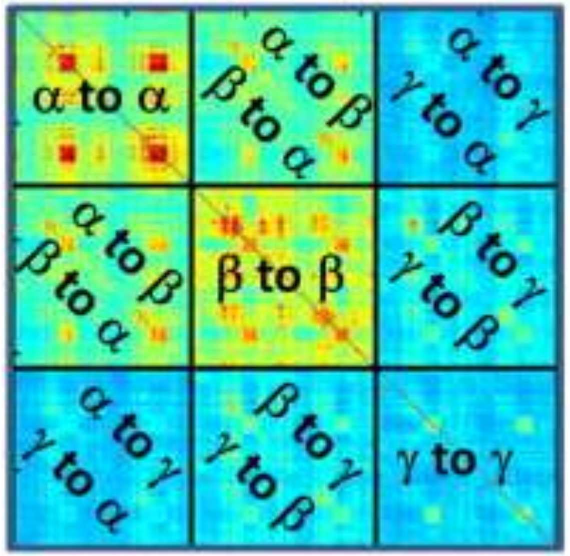
Dynamic Functional Connectivity (DFC) provides the solution to observe the fluctuations and dynamic reorganization of the brain network over time. It allows to track the information flow and dynamic reconfiguration of the modular structure in the brain. This provides a better understanding of the neural mechanisms both during rest and task based conditions.

Preti et al., NeuroImage, 2016
Ren et al., IEEE TNSRE, 2017
Bassett et al., PLOS Comp. Bio., 2013

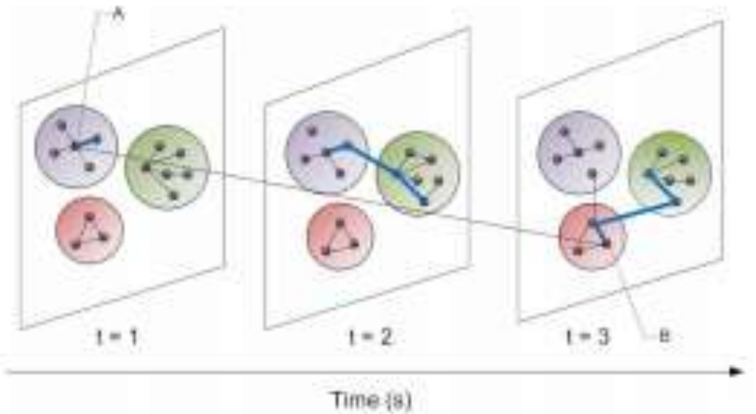
Multilayer Network

Multilayer network allows to model multiple domains like spatial, temporal and spectral, in an unified framework. Two representation of multilayer network are mostly studied:

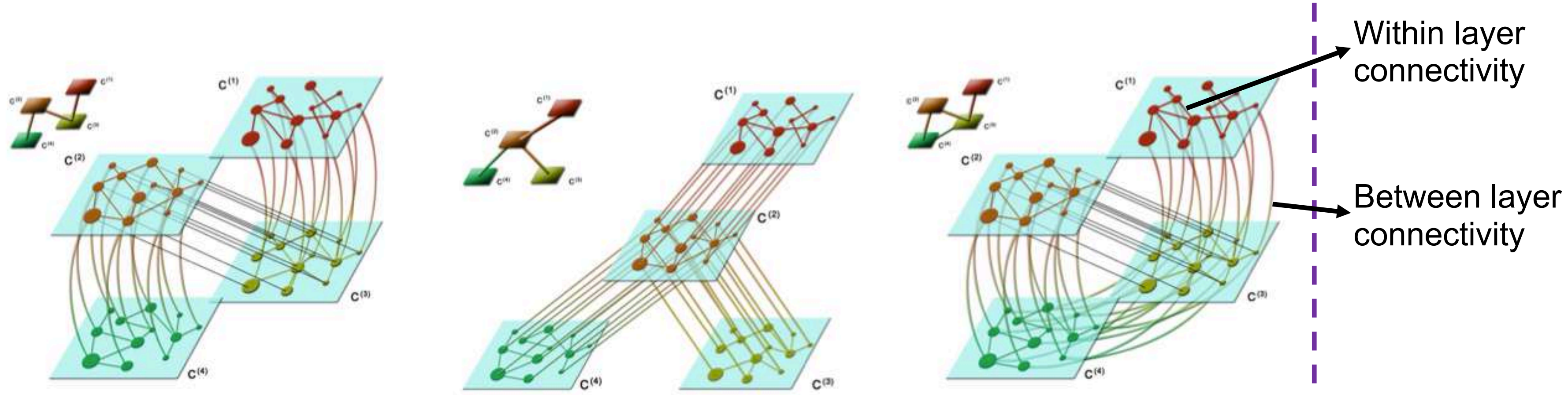
- Tensorial Representation- Layers are stacked and nodes are both connected at intra-layer and/or inter-layer. Mostly used for dynamic functional connectivity analysis.
- Supra-adjacency matrix- Flattened representation of multilayer network where individual adjacency matrix together forms the supra-adjacency matrix. It is mostly used for within and cross frequency coupling.



Supra-adjacency matrix



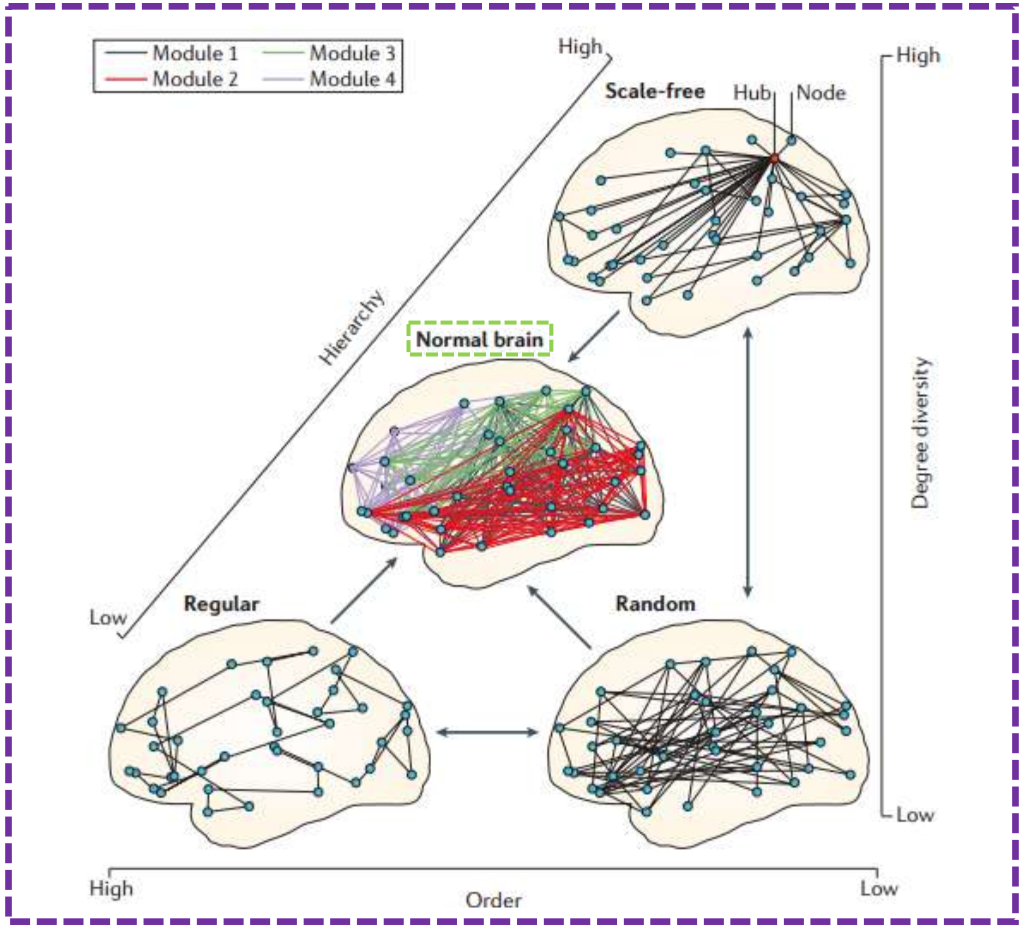
Tensorial Representation



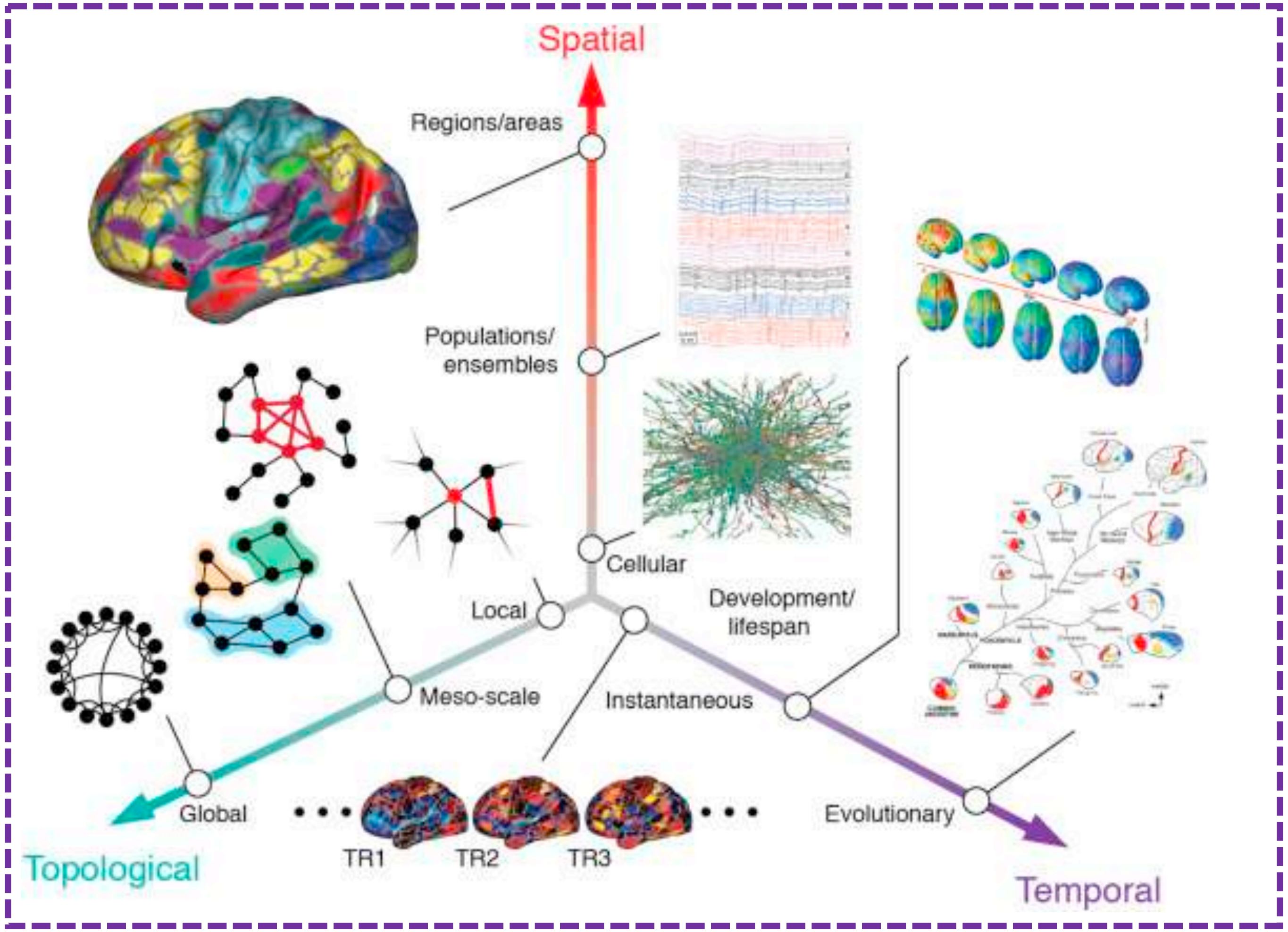
Example of Multilayer Network Connectivity

Ren et al., IEEE TNSRE, 2017
Brookes et al., NeuroImage, 2016

Brain at Multiple Scales



Intermediate structure organization of normal brain network

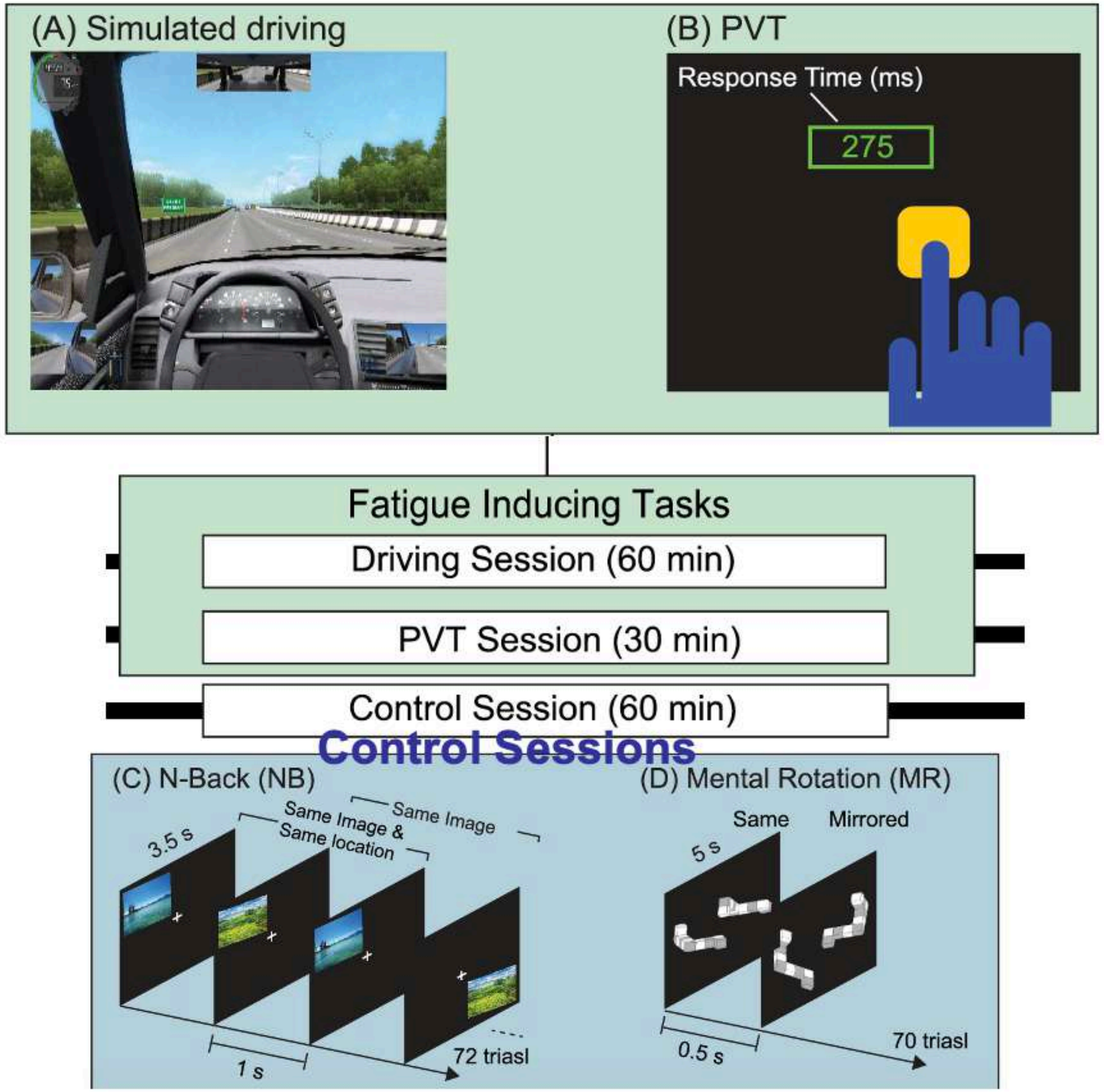


Organization of brain networks in Spatial, Topological and Temporal scales

- The need of graph theory is due to a paradigm shift in brain function, which has been observed from localized populations of neurons to the importance of connectivity between the brain regions (Bassett et al., 2006; Park et al., 2013)
- The brain networks is also a composite mixture of ‘random’, ‘regular’ and ‘scale-free’ networks
- The brain networks are fundamentally based on multiple scales: Spatial, Topological and Temporal scales (Betzel et al., 2017)
- Hence, for real-time effective tracking of cognitive states, an advanced framework incorporating multiple scales of brain network is essential

Cornelis, Nature, 2014
Betzel et al., NeuroImage, 2017

Driving vs Psychomotor Vigilance Task vs N-Back and Mental Rotation (Fatigue and Cognitive Workload of Drivers)



Experimental Design:

- 2D environment (CityCar software)
- 64 channel wet electrode EEG
- Pre- and post-task behavioral analysis
- Fatigue induced via two **different tasks (driving and PVT)**

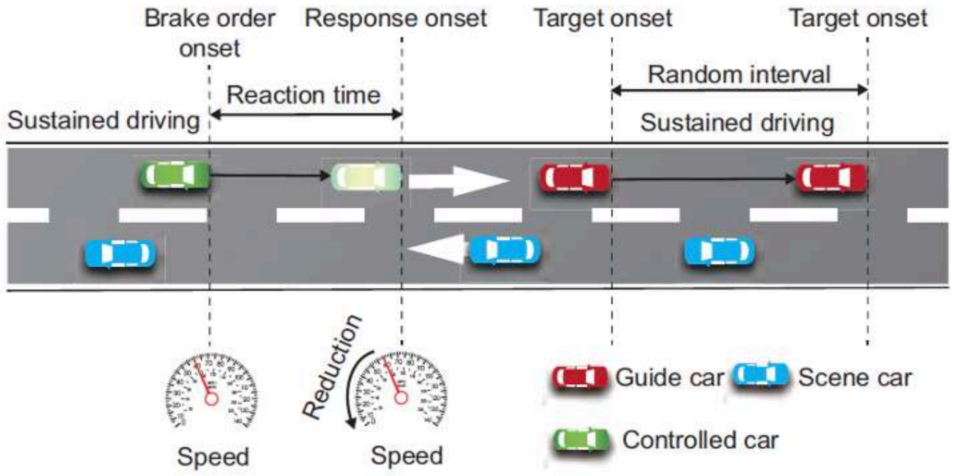
EEG metrics:

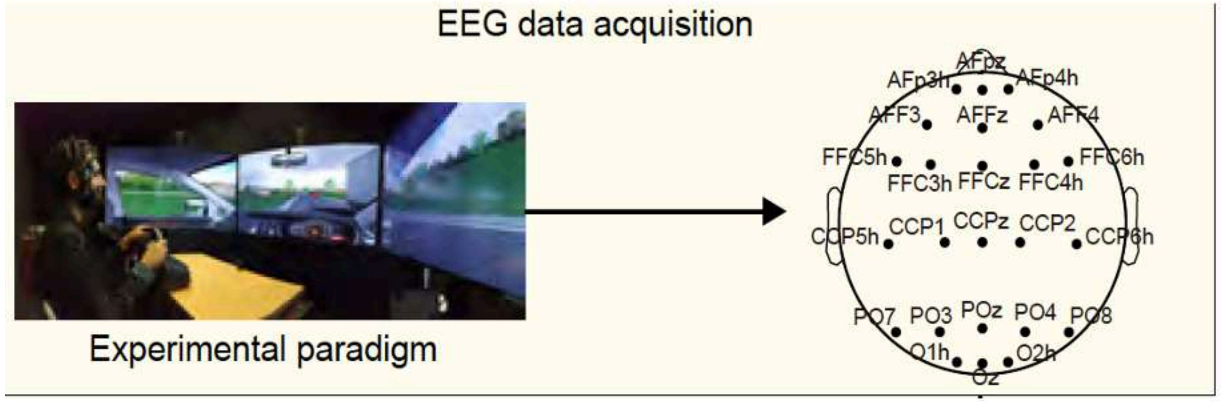
- Theta frequency band (4-7Hz)
- Functional connectivity network analysis
- Graph theory metrics: clustering coefficient; path length
- **Classification accuracy**:

- driving = 0.921 (sensitivity = 0.947, specificity = 0.895) (p < 0:001)
- - PVT= 0.974 (sensitivity = 1, specificity = 0.9474) (p < 0:001)

(Dimitrakopoulos et al., 2018 IEEE TNSRE)

Dynamic Monotoring the Fatigue Induced by Monotonic Driving Task





➢ Experimental Design:

- 20 subjects;
- 24 channel dry wireless EEG
- Pre- and post-task behavioral analysis
- 3D " environment by 3 60" TV
- CityCar software;
- Logitech G27 Racing Wheel simulator)

➢ EEG metrics:

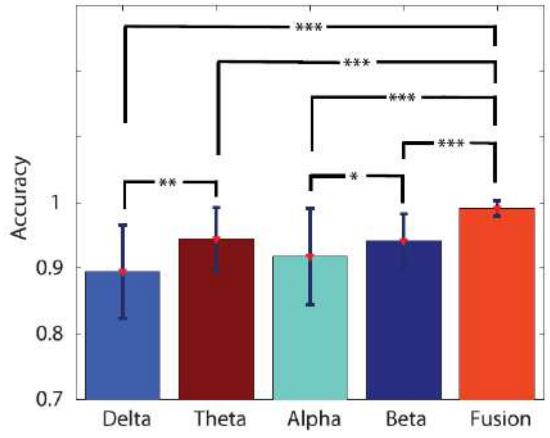
- Theta (4-7Hz), alpha (8-15Hz) and
- beta (14-30Hz) frequency bands
- **4 sec** temporal resolution
- **Temporal functional connectivity**
- **Frontal and parietal** lobes are affected by fatigue

(Wang et al., 2020 IEEE TNSRE)

Multimodal (EEG + EOG) Classification of Driving Fatigue

➢ Experimental Design:

- 22 subjects; 3D environment (CityCar software)
- 24 channel dry wireless EEG
- Pre- and post-task behavioral analysis
- Fatigue induced via driving task (3D environment (CityCar software; Logitech G27 Racing Wheel simulator)



Max Accuracy: 99.1 ±1.2%

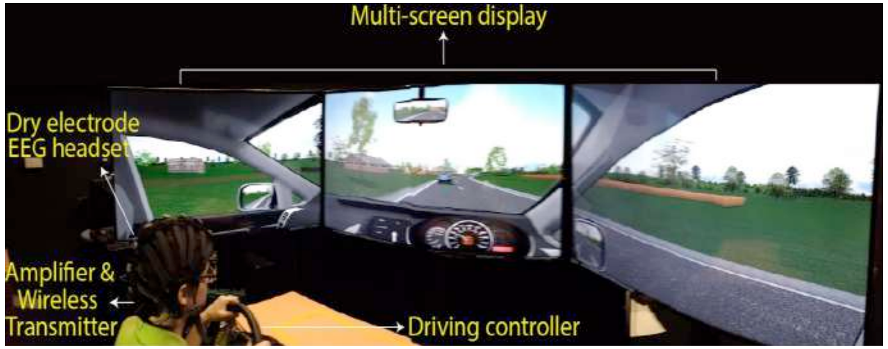
➢ EEG metrics:

- Information theoretic features extracted from EOG (sample entropy) and EEG
- (approximate, sample and spectral entropy)
- Delta (1-4Hz), theta (4-7Hz), alpha (8-15Hz) and beta (14-30Hz) frequency bands
- Feature fusion via canonical correlation analysis ((

FIGURE 1. The simulated driving system used for the implementation of the proposed protocol.

(Wang et al., 2018 IEEE Access)

Practical and Real-Time Implementation of EEG-based Driving Fatigue Estimation



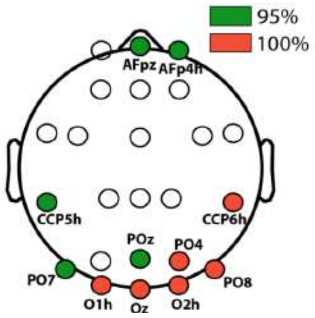
➢ Experimental Design:

- 22 subjects; 3D environment (CityCar software)
- 24 channel dry wireless EEG
- Two experimental sessions (1 week apart): one used for training the model; the second for fatigue estimation

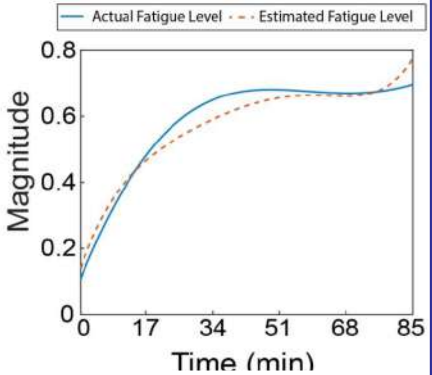
➢ Methodology: Study I

- Regression analysis used for **continuous fatigue level estimation**
- Dynamic Time Warping (DTW) used instead of RT
- 5 sec time resolution

(Bose et al., 2019 IEEE Cog Dev Syst)



Electrode	Frequency Bands
AFpz	θ/β
AFp4h	α
CCP5h	β
CCP6h	γ
POz	θ/β
PO4	β
PO7	γ
O1h	β
Oz	δ, α, β, θ/β
O2h	θ/β
PO8	θ/β



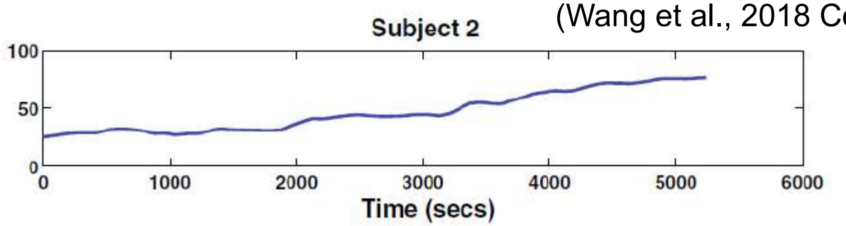
Reduced set of EEG electrodes used for fatigue estimation

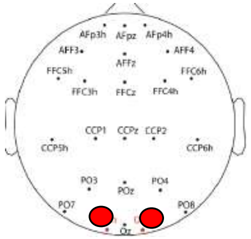
Regression based fatigue estimation

Study II

- **Real-Time Fatigue Estimation**
- Sample entropy and power spectral density used as metrics
- 2 EEG channels in the occipital lobe (O1 and O2)
- 10 sec time resolution

(Wang et al., 2018 Cognitive Neuro)





Continuous time estimation

$$Integrated\ metric = \frac{1}{2} * \left(\sum_{n=1}^{n} \frac{PSD_\theta(n) + PSD_\alpha(n)}{PSD_\beta(n)} + \sum_{m=1}^{m} \frac{PSD_\theta(m)}{PSD_\beta(m)} \right)$$

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