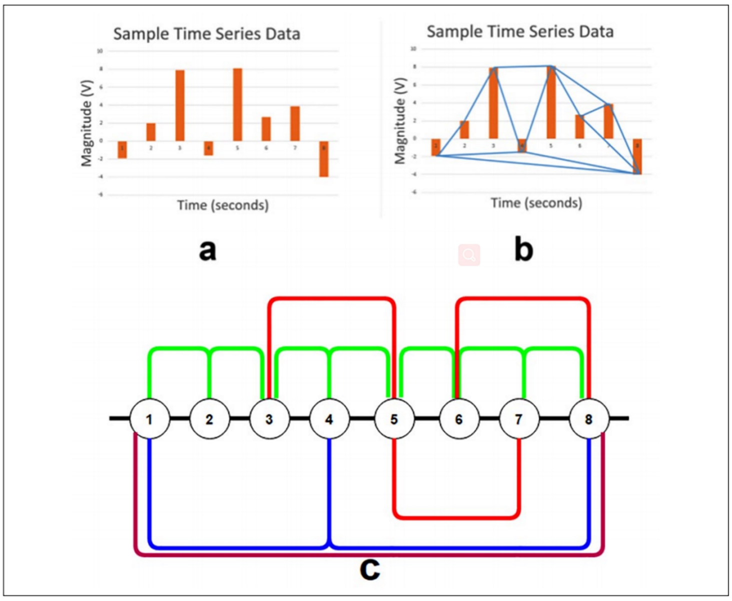
ReadingNotes1

2021年9月9日 7:55

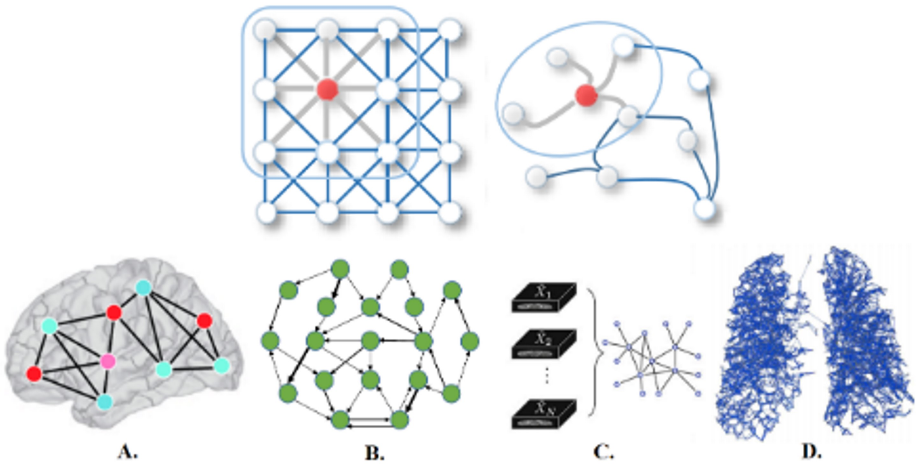
1. **Paper Title "Graph Theory and Brain Connectivity in Alzheimer's Disease"**

- Foundations of Graph Theory
    - Definition
    - Matrix Representation of Graphs
    - Visibility Graph
    - 

    - Improved Visibility Graph (denoised)
    - Hubs (Highly connected regions of a network)
        - Produce scale-free networks
        - Derive from [fractal system]
    - Small worldness
        - Modeled by <u>clustering coefficient</u> and <u>characteristic path length</u>
            - <u>First</u> is showing how densely confined and connected local nodes are.
            - <u>Second</u> is the disctence between connected clusters which can quantify connectivity.
    - Global and local changes
        - Global connectivity: adjacency status
        - Local connectivity: connection strength
        - Changes on this two aspects
    - Other methods
        - Granger causality
        - Wavelet analysis
        - Spectral coherence
        - Entropy
        - Synchronization likelihood
- Connectivity changes as a biomarker
    - Functional connectivity changes are prevalent in disease.
        - Decrease is a viable biomarker.
    - fMRI is commonly used to examine brain networks.
        - Default mode network (DMN)
        - Sensorimotor network (SMN)
        - Salience network (SN)
    - Local Regions
    - Default Mode Network

    - Global Connectivity
    - Electroencephalography
    - Small Worldness

2. Paper Title " Graph-Based Deep Learning for Medical Diagnosis and Analysis: Past, Present and Future"

- Introduction
    - Why graph deep learning for medical diagnosis and analysis
        - Traditional neural networks can not capture local and global connectivity.
        - Graph deep learning can.
        - Many physical human processes generate data that is naturally embedded in a graph structure.
    - 

    - Several application domains
        - Brain activity analysis
            - Brain signal: Brain signals are an example of a graph signal, and the graph representation can encode the complex structure of the brain to represent either physical or functional connectivity across different brain regions. At the structural level, the network is defined by the anatomical connections between regions of brain tissue. At the functional level, the graph nodes represent brain regions of interest (ROI), while edges capture the correlation between their activities computed via an fMRI correlation matrix.
            - GCNs offer advantages when dealing with discriminative feature extraction from signals in the discrete spatial domain, and for applications such as EEG analysis can capture hidden relationships among EEG signals from different channels.
            - GCNs provide an effective way to discover and model this intrinsic relationship between different nodes of the graph or contacts.
            - GNN models also offer advantages when considering the need to develop deep-learning scoring models which allow a direct interpretation of non-Euclidean spaces. This explanation can help to identify and localize regions relevant to a model's decisions for a particular task. An example is how certain brain regions are related to a specific neurological disorder, which are defined as biomarkers.
        - Brain surface representation
            - GCNs, however, can be applied to graphs with varying numbers of nodes and connectivity. Spherical CNN architectures can render valid parametrizations in the spherical space without introducing spatial distortions on the sphere (spherical mapping), and geometric features can be augmented by utilizing surface registration methods.
            - GCNs can also offer more flexibility to parcellate the cerebral cortex (surface segmentation) by providing better generalization on target-domain datasets where surface data is aligned differently, without the

need for manual annotations or explicit alignment of these surfaces.

        - Segmentation and labeling of anatomical structures
        - Multi-modal medical data analysis

- Graph Neural Networks
    - Overview --how Graph Neural Networks developed
    - Graph construction and traditional framework
    - Spectral-GCNs
    - Spatial-GNNs
    - Graph networks with temporal dependency
        - RNN-based
        - CNN-based
    - Graph networks with attention mechanism
- Case studies