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Applications of Graph Theory in Biology and Construction

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ABSTRACT
The aim of this paper is to brief the applications of graph Theory in the field of medicine. In particular, in biological neural networks like brain function connectivity, amygdalar network and components in major depression disorder. We also discuss an interesting and new application of graph theory, that is in the field of Construction.

KEYWORDS: Graph Properties, Graph Neural Network, Biological Neural networks, Amygdalar network.

INTRODUCTION

Although the birth of Graph Theory can be stated back to late 1950's, it emerged as a widely applicable field and developed as a very useful tool from past 100 years. One such widely used and a very useful field of application is medical field. In various industries like chemistry, biology and transportation deep learning has attained a remarkable success. Traditional neural networks such as CNN-convolution neural network, RNN-recurrent neural network and DNN-deep neural network are able to process data structures with fixed forms like images, text but they do not deal with graphs. A graph is a mathematical structure which consists of unordered nodes and edges which are variable in nature. Graphs are used in various fields to represent different types of data. In reasoning and representation of knowledge, topological structures of knowledge bases are presented by knowledge graphs. During recent years, due to the convincing performance in processing graphs, graph theory has found its notable attention in the field of GNN-Graph neural networks. Graph neural network have proved the potential to solve the complex problems in many fields. GNNs are used to predict the side effects caused by multiple drugs combinations in the field of medicine. To predict chemical properties based on the molecular structure, in Chemistry GNN is adopted. GNN have gained enormous attention in the field of construction, with their primary uses in clustering of building groups into irregular and regular patterns through unsupervised learning. In the construction [7] to handle Euclidean data effectively, GNN have emerged as a promising solution which includes floor plan design, bridge inspection, building information models (BIM) and scanned point clouds. However, despite their potential, there is a lack of comprehensive scholarly work providing a holistic understanding of the application of GNNs in the construction domain. Several surveys are conducted by the researchers in the field of computer science on GNN. By these surveys one can suggest that GNN can be a powerful tool to process graph-structured data and their applications apart from the field of computer science, which are rapidly developing in the present scenario. These Reviews focussed primarily on computer science and computer vision, drug design, Natural Language processing, social networks, citation networks, molecular biology, power systems, traffic forecasting and construct field. A GNN is a class of artificial neural network for processing the data that can be represented as graphs. ANN-Artificial neural network also called NN-Neural Network or Neural Net is an algorithmic process of biological neural networks that constitute animal brain. In all vertebrates and in most of the invertebrates an organ that serves as the centre of nervous system is a brain, which is located close to the sensory organ for vision. It is a very complex organ in vertebrate's body. A human brain contains cerebral cortex that contains approximately 14 billion to 16 billion neurons [1] and estimated number of neurons in the cerebellum is 55-70 billion [2]. A brain-computer interface (BCI) also called a brain-machine interface (BMI) or Smart brain is a direct communication pathway between brain electrical activity and a machine i.e a computer or a robotic limb. Implementation of BCI are often directed at researching, mapping, assisting augmenting or repairing human cognitive or sensory- motor functions. BCI implementation range from non-invasive methods like EEG,MEG,MRI,EOG and partially invasive methods like ECoG- and Endovascular to invasive method like microelectrode array, based on how close the electrodes are to the brain tissue[3]. application of graph theory methods has provided valuable insights into the dynamic nature of functional connectivity in the brain. As research continues in this area, it is likely that we will gain a deeper understanding of the brain's organization and how it contributes to various cognitive processes.

Applications of graph theory in biology

Recent advancements in neuroimaging have made it possible to investigate the structural and functional connectivity between different regions of the brain in vivo. This has allowed researchers to better understand the complex neural networks that underlie a wide range of cognitive processes. One important finding from this research is the central role that hub nodes play in brain communication and neural integration. Such high centrality, however, makes hub nodes particularly susceptible to pathological network alterations and the identification of hub nodes from brain networks has attracted much attention in neuroimaging. Current popular hub identification methods often work in a univariate manner, i.e., selecting the hub nodes one after another based on either heuristic of the connectivity profile at each node or predefined settings of network modules. Connector hubs play a significant role in maintaining the network's integrity by facilitating communication between different modules. Thus, the identification of connector hubs is critical for understanding the network's overall function. However, most current methods focus on identifying provincial hubs.

The application of graph theory methods has allowed researchers to better understand the complex dynamics of the brain and how it responds to different stimuli. These methods have proven useful in a wide range of studies, including those focused on understanding the neural basis of various mental disorders such as schizophrenia and depression. Wenjing Luo , et.al.,[5] have found that functional connectivity in the brain is a topic of great interest in the field of neuroscience. To date, studies in this area have relied on fixed nodes to define brain regions. However, recent research has shown that using fixed, group-specific, state-specific, and individualized parcellations to define nodes can significantly influence findings at the network level. There are instances where changes that are typically reported are not persistent and are dependent on the state or group. This means that the changes are only observed when there are node reconfigurations. It is important to note that some changes are only temporary and may not necessarily be indicative of a long-term shift. In these cases, it is crucial to gather more data and analyze the situation thoroughly before making any decisions or drawing any conclusions. Understanding the factors that contribute to these state- or group-dependent changes is essential in determining their significance and potential impact on the system as a whole. Overall, these findings highlight the importance of considering the underlying structural changes that occur in the brain when interpreting graph theory results. By taking a more nuanced approach to analyzing these changes, researchers can better understand the complex connectivity patterns that underlie brain function and disfunction.

Saba Amiri et.al[4] have discussed the brain functional connectivity (FC) with the application of graph theory. In individuals to the study PNES-psychogenic nonepileptic seizures can, Graph theory provide valuable insights into the mechanisms underlying in this disorder. By analysing brain networks and their activity during PNES episodes, researchers can identify specific regions or networks that are disrupted and gain a better understanding of the underlying mechanisms. This knowledge can ultimately lead to more effective treatments for individuals with PNES. The results of the study showed significant alterations in FC within the whole brain in patients with PNES compared to healthy control subjects. The findings suggest that there are differences in the way that different regions of the brain communicate with one another in individuals with PNES. The study aimed to investigate the nodal degree in both cortical and subcortical regions of the brain, which is a significant feature of the graph theory. The nodal degree is an indicator of the number of connections that a node has with other nodes in a network. In this study, we calculated the nodal degree for all cortical and subcortical regions in the brain. The findings of this study suggest that there may be a neurological basis for the development of PNES, and that further research is needed to fully understand the relationship between hyper-connectivity in these specific areas of the brain and the manifestation of PNES. These findings may also have implications for the development of potential treatments for PNES, as they provide insight into potential targets for intervention. The study conducted revealed that there was a decreased nodal degree or hypo-connectivity in various brain regions. Specifically, the left and right insula (INS), the right putamen (PUT), and the right middle occipital gyrus (MOG) were found to have a lesser nodal degree. This information is significant as it provides insight into the connectivity and functioning of different areas of the brain.

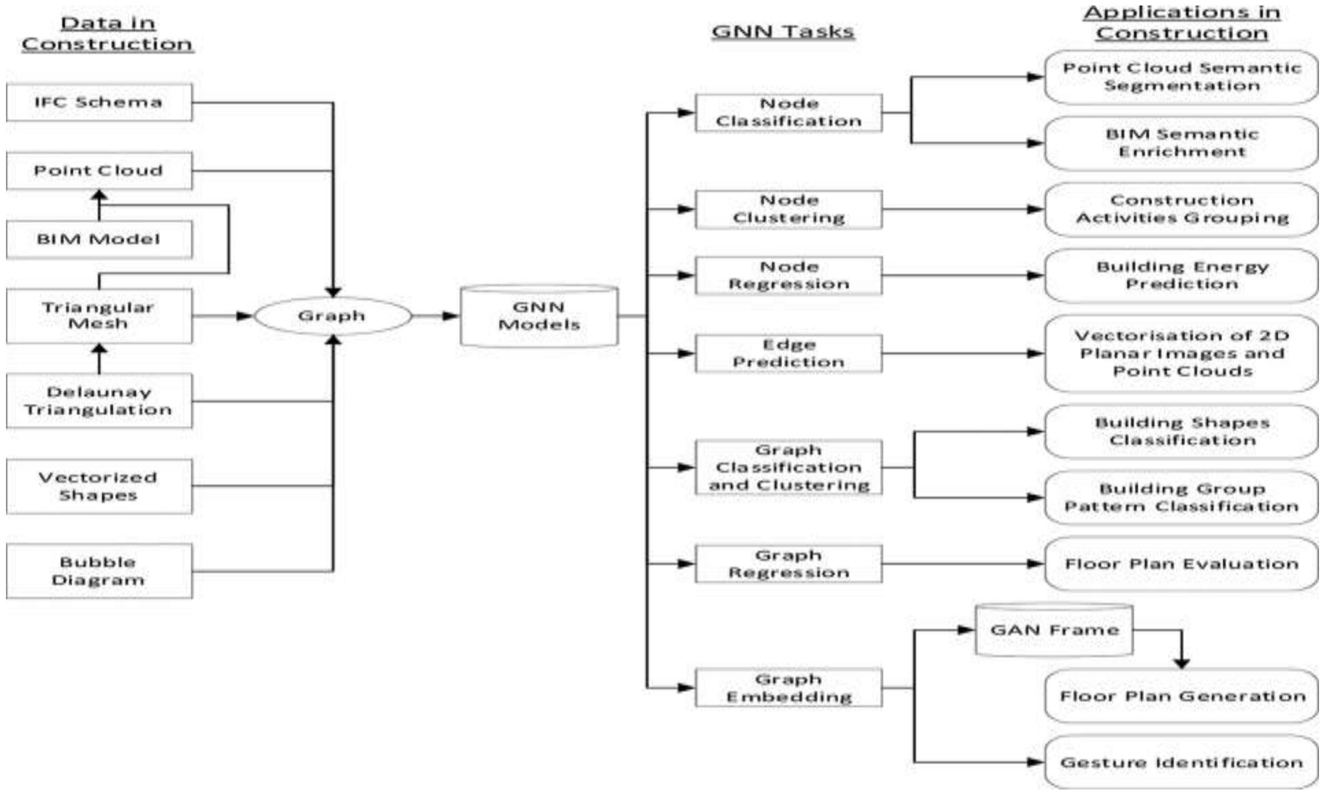
Effective amygdalar functionality depends on the concerted activity of a complex network of regions. Thus, the role of the amygdala cannot be fully understood without identifying the set of brain structures that allow the processes performed by the amygdala to emerge. However, this identification has yet to occur, hampering our ability to understand both normative and pathological processes that rely on the amygdala. We developed and applied novel graph theory methods to diffusion-based anatomical networks in a large sample (n = 1,052, 54.28% female, mean age=28.75) to identify nodes that critically support amygdalar interactions with the larger brain network.

Melanie A. Matyi , et.al.,[7] three graph properties, each indexing a different emergent aspect of amygdalar network communication: current-flow betweenness centrality (amygdalar influence on information flowing between other pairs of nodes), node communicability (clarity of communication between the amygdala and other nodes), and subgraph centrality (amygdalar influence over local network processing). Findings demonstrate that each of these aspects of amygdalar communication is associated with separable sets of regions and, in some cases, these sets map onto previously identified sub-circuits. For example, betweenness and communicability were each associated with different sub-circuits that have been identified in previous work as supporting distinct aspects of memory-guided behavior. Other regions identified span basic (e.g., visual cortex) to higher-order (e.g., insula) sensory processing and executive functions (e.g., dorsolateral prefrontal cortex). Present findings expand our current understanding of amygdalar function by showing that there is no single ‘amygdala network’, but rather multiple networks, each supporting different modes of amygdalar interaction with the larger brain network. Additionally, our novel method allowed for the identification of how such regions support the amygdala, which has not been previously explored.

More than 9% of global population across diverse countries might suffer from major depressive episode and related hardships of role performance at least once in their lifetime [9]. For better understanding of the neural correlates of clinical symptoms, treatment response, and disease prognosis for major depressive disorder (MDD), brain magnetic resonance imaging (MRI) have been widely used.In order to understand the organizational styles of neural underpinning in major depressive disorder (MDD), a review of recent neuroimaging studies (published during 2015-2020) that utilized a graph theory approach to the diffusion tensor imaging data or functional brain activation data acquired during task-free resting state was conducted. This approach allowed researchers to analyze the connections between different brain regions to determine how they contribute to the development and manifestation of MDD. Depending on age and medication status, there was a diversity in the global organisation of resting state functional connectivity networks for MDD. Intra-modular functional connections were weaker in MDD compared to healthy controls (HC) for default mode and limbic networks. In comparison to the HC, we also found lower local graph metrics of default mode, frontoparietal and salience network components in MDD. In the MDD, we also found weak local graph metrics for default mode, frontoparietal and salience network components compared to HC. In contrast, a higher local graph score of MDD compared to HC is shown for brain regions comprising limbic, sensorimotor and subcortical networks. For the brain white matter-based structural connectivity network, the global network organization was comparable to HC in adult MDD but was attenuated in late-life depression. The severity of depressive symptoms, the burden of perceived stress and treatment effects have had a positive influence on local graph metrics for limbic, susceptibility, default mode, subcortical, insular or frontoparietal network components in structural connectome. Overall, the current review revealed that MDD compared to HC has a change in global network organization of structural and functional neural connectomes as regards baseline age and medication status. Collectively, the current review illustrated changed global network organization of structural and functional brain connectomes in MDD compared to HC and were varied according to the onset age and medication status. The MDD has a weaker intermodular functional connectivity compared to HC when it comes to default mode and limbic networks. Local graph metrics of structural connectome for MDD reflected severity of depressive symptom and perceived stress, and were also changed after treatments. Je-Yeon Yun et. al., [8] have explored the graph metrics-based neural correlates of clinical features, cognitive styles, treatment response and prognosis in MDD are required.

Applications of graph theory in construction

The adoption of GNNs in the field of construction emerged in 2018 and is still in its infancy. In order to tackle the challenges that cannot be dealt with in an effective manner by traditional Deep Learning models, there is increasing interest in using Global Navigation Satellite Systems within the construction sector. An overview on the different and new uses of Geotechnical Navigational Networks in construction is presented in this review. Although research in the field of GNNs has yet to be fully explored, a growing number of studies on GNIs in construction show increased interest and provide new opportunities for future developments. Yilong Jia et.al., [6] have conducted a systematic review following the PRISMA framework to obtain a comprehensive understanding of the status quo of GNNs in the construction context. Illustration of the graphical abstract [6] is illustrated below.



The most common problem with the development of diagrams is that it often takes a manual process, involving tasks like converting BIM models into point clouds, trigonometric mesh to Point Clouds, floor plan for bubble diagrams and geometric primitives on graphs. These activities may take time and are prone to error, which could adversely affect the quality of a dataset being prepared. Additionally, this manual process can become ease when creating large-scale datasets or when working with real-time problems.

CONCLUSION

In this review, we have tried to give a glimpse of the applications of graph theory in biological neural networks and also in the field construction.

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