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Uncovering Brain Chaos with Hypergraph-Based Framework

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Abstract: The scientist has proven that the birth of neurons in a region of adult rat brain migrates from their birthplace to other parts of the brain. The same process also happens in adult humans. There was no efficient visualization tool to view the functions and structures of the human brain. In this paper, we focus to design a framework to understand more about Alzheimer's disease and its process of neurons in the human brain. This framework named a hypergraph-based neuron reconstruction framework. It helped to map, the birth and death of neurons with the construction and reconstruction of the hypergraph. This framework also recognizes the structural changes during the life cycle of the neuron. Its performance was evaluated quantitatively with small-world networks and robust connectivity measures.

Index Terms: Hypergraph, multi-level neuron, brain disorder, visualization, communication network.

1. Introduction

Neuron connectome construction was an idea of constructing a small working computer model of a brain. Connectome was the complete description of the structural connections between elements of a nervous system [1]. Over the past hundred years, biological research has accumulated an enormous amount of detailed knowledge about the structure and functions of the human brain. Neuron connections are extremely entangled, and its connectome was not inferred until now. Graph theory-based focus could provide a powerful and better way to analyze the complex networks of the brain and to quantify its structural and functional systems [2, 3]. Three important issues based on brain network were mentioned by Wang Z. et al. in his novel approach of hypergraph model for brain network. One of the issues was addressed here. It was that there was a need to investigate the compound hyper-structure through the hypergraph model and to understand the properties of the brain [4]. In this paper, one of the properties of the neuron called conductivity was modeled using a hypergraph. The conductivity of nerve cells in the central nervous system responds to stimuli by producing electrical signals that are quickly conducted to other cells at distant locations. That is, a signal passes from one neuron to another neuron, which maps to the path in the graph. Other properties such as creation and migration of a new neuron, finding a path between available neurons, communication between multiple neurons with each other, and ideal or the dead neuron, were modeled in this hypergraph-based neuron reconstruction framework [5, 6]. The framework based on visualization. It helps to visualize the brain images, to convey complex information in a simple way. The brain image viewed as a hypergraph or incidence structure, which was implemented as an incident matrix. Few neurons die during the migration and other few neurons don't reach its destination. These unnatural behaviors lead to brain disease in human beings like Parkinson's disease, and Alzheimer's disease. Alzheimer's disease is a key challenge for 21st-century healthcare. During the course of Alzheimer's disease, nerve cells die in particular regions of the brain. So, there is a need for physicians to spot the live or dead neuron to predict the presence of Alzheimer's disease. The brain image of normal and Alzheimer's disease subjects was chosen for the experimental study in section 3. The tools and resources needed for the implementation were specified in section 4. Hypergraph information was compiled with 'CSV' file format and it was discussed in section 5. In section 6, matrices and the corresponding output picture were clearly shown. Time complexity was chosen as a performance measure, and its evaluated results were also shown. The limitation to overcome in near future was given in section 7 with summary of the work done.

2. Related Work

The neuropsychiatric disease was a burden for the neurologist, neurosurgeons, and neurophysiologists, and it was increasing rapidly worldwide [7, 8]. With that understanding brain circuits were a key challenge over the last decade. Active researchers focus on nerve cell movements inside the brain through alternative treatment such as brain simulation and functional imaging [9, 10]. Recent technologies like artificial intelligence, deep learning helped to create smart and intelligent medical products, where the neurologist can apply diagnosis and prevention of brain diseases [11, 12]. Through advances in the neural network, so many neuroscience challenges like understanding brain pathways, the complex network connectivity was made easy [13]. Simulation became an important part of the treatment modality for severe Alzheimer's disease, Parkinson's disease, dystonia, and tremors. So many simulation research tools also have been emerged for the use of physicians. Brain stimulation technologies activate the action-dependent transform in neuronal function. But simulation techniques need significant computing power, leads to development in supercomputing and programming like CUDA using GPU [14]. The significance of higher-layer brain structures was analyzed in a different activity. The brain connectivity structure was shown using clusters [15]. The number of edges and vertices in the hypergraph cluster increases based on the size of connections in the network. To further increase the connection pathways to trillion nodes; it is the superlative prime way to utilize the supercomputers in India. Nowadays, the powerful mainframe computer with more than millions of cores were competing together to operate like a human brain [16]. The diagnosis of Alzheimer's disease (AD) is one of the current active research. It was essential to deal with missing data and deficient data of several methods in a sparse environment. View-aligned hypergraph learning was introduced. Here the hypergraph was constructed based on each view or modality [17]. Hypergraph was studied in discrete mathematics and in statistic image classification. Since it provides an organized representation of information [18]. Hypergraph learning generates edges by linking images and their nearest neighbors. A set of edges were formed using the varying size of the image neighborhood [19]. So, to attain good performance in structuring information, any brain image should be transformed into a hypergraph model. Still, there was a necessity to understand the complex structure of the brain. So the idea was to split the whole structure into smaller units for better understanding. Tools should be developed to view and analyze those small units in a detailed approach [20]. Even though other fields have suggested a lot of approaches for analysis and visualization of data, the neuroscience community requires novel tools and algorithms for their special-purpose usage. Tools use data for navigation, manipulation, comparison, and integration. It helps to represent higher-order data. It also helps to extract principles and accumulate data among many levels of study. Over the years, these tools benefit the researchers in branches of the computer sciences since they deal with concerns related to brain function such as robotic pathfinding and robotic task planning [21]. Medical images present a good description when it is in a sparse matrix. The communication among all nodes was very complex. The hypergraph clustering approach introduced for the concept of network centrality, which is an in supra-dyadic nature. The real problem was the development of brain network nodes and their communication. Developed countries were working on this problem of computational neuroscience through scientific institutions and research organizations [22]. The computer model of a brain also provides awareness to other fields of research like drug discovery. The brain model helps to identify the drugs for diagnosis and treatment methods. Eventually, through this, the patients will get drugs and advanced medical options at a lower cost [23]. Corinne Teeter was mentioned that there was a need to make a simple linear model with a unique parameter to classify multiple types of the neuron [24]. Olaf Sporns also stated that there was a strong demand for graph theory-based tools to analyze brain network data [25]. It shows the importance of designing a computer model to construct and compute the neurons' structural changes. Such a model will help medical researchers to study brain diseases and disorders. It motivated to create an efficient and effective model to visualize and evaluate the human brain structure [26]. Visualization also plays a vital role in the diagnosis of brain disorders like Alzheimer's disease. The most important aspect of the visualization was to integrate the structural property of the human brain. To diagnose brain disease through image-based techniques, this visualization helps to identify a different feature in all possible ways [27]. The human brain project enlightens a demand for effective visualization and efficient evaluation tool to view the structure of the human brain [28]. Structural information of the brain can be best visualized using diagrams of abstract graphs and networks. Many open-source visualization tools were available for researchers and end-users, like Graphviz, Lucidchart and Dia [29]. But there is no such tool that can cover many vertexes into one edge. And also importantly, there was no tool available for researchers to draw the scattered vertices covered by a single edge. So there was a need to display the hypergraph structure in an interactive graph browser with multiple options such as fonts, colors, and shapes. The reason for choosing a hypergraph was that it has sparse representation for the image and its set, subset, and family of the set can be shown clearly using the Tikz package of Latex. In this paper, the idea of designing a framework was to investigate and to visualize the compound hyper-structure of a brain, which will help the neuroscientists and neurologists in small labs to have a better view of the structure of the neuron.

3. Hypergraph-based Neuron Reconstruction Framework

3.1. Preliminaries

Brain network was a system that could acknowledge the mathematical representation as a graph whose vertices will identify the elements of the system and the edges represent the presence of relationships among those elements. An edge is an incident on a vertex if the vertex is one of its endpoints. A vertex is an incident on an edge if it is one of the endpoints of the edge. Since vertices and edges of high-level abstraction will help to apply to a huge vector of systems. The network-based framework will allow the mapping of interactions among interrelations in complex systems.

An undirected graph is a pair G= (V, E) where V is a set of nodes and $E \subseteq \binom{v}{2}$ is a set of edges. Hypergraph in Fig.1 was defined by an incidence matrix $A = \left(a_j^i\right)$ with a column representing edges $r_1, r_2, \ldots, r_m$ and row representing vertices $n_1, n_2, \ldots, n_n$, where $\left(a_j^i\right) = 0$ if $n_i \notin r_j$ and $\left(a_j^i\right) = 1$ if $n_i \in r_j$ [30,31].

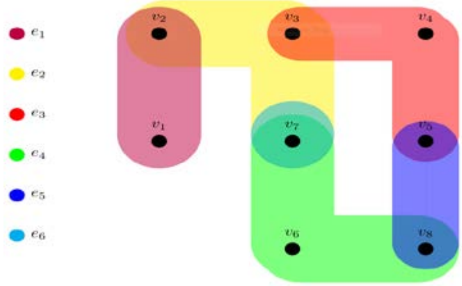

Fig.1. Simple Hypergraph Structure created with tikz

The robust network of the brain can be viewed as a brawny hypergraph structure. Vertices were considered as neuron $\{n_1, n_2, \ldots, n_i\}$ and edges were considered as brain regions $\{r_1, r_2, \ldots r_j\}$ Where i, j – total number of vertices or edges (neurons and brain region) respectively.

Hypergraph Coloring Theorem:

A hypergraph good λ-coloring of H is a partition of V into λ a stable set $S_i (i = 1, 2, ..., \lambda)$ such that each edge E_j has min $\{|E_j|, \lambda\}$ colors.

3.2. Contribution of the framework

1. Loading the vertices and edges to create a new hypergraph structure.
2. Add new vertices and edges in the generated hypergraph structure.
3. Delete the ideal and unnecessary vertices from multiple edges.
4. Check for an empty edge and remove it from the structure.
5. Mapping path to created vertices using edges (also called conductivity)
6. Conductivity is shown using multiple colors.

3.3. Process of hypergraph-based neuron reconstruction Framework

Initially, the first vertex was created to represent a new neuron. This first vertex (N_1) will be inside the first edge (R_1). When the second vertex (N_2) was created, a pathway was generated between two neurons, which form a neural circuit [32]. The second vertex can be inside the same first edge (R_1) or can be a new edge (R_2). If it was between the two new edges, then the neurons form a message flow path among the two dissimilar regions of the brain.

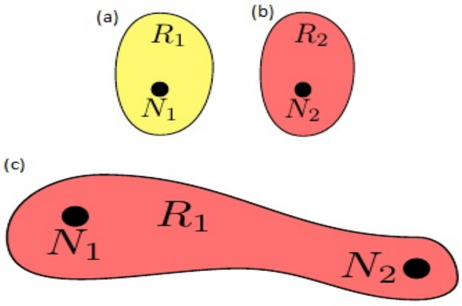

Fig.2. (a-c) Birth of neurons and the formation of regions

Likewise, the next neuron and the vertex were created along the region of the brain or along the edges, shown in Fig 2 (a-c).

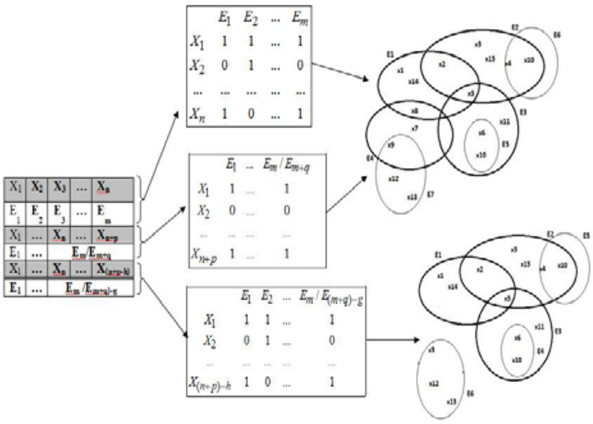

Fig.3. Process of hypergraph-based neuron reconstruction Framework

Similarly using algorithm 1, the fundamental construction of basic hypergraph of 'N x M' matrix was done, where N represents the base index of vertices and M base index of edges. The overall process was shown in Fig 3.

Algorithm 1 Loading and Constructing Hypergraph

1. Input I_v and I_e; // I_v and I_e represent the index sets of the vertices and the edges, respectively.
2. Input vertices x_i and its corresponding edge set e_i .
3. Vertices collected in the form of a vector,

$$X \leftarrow \{x_i \mid i \in I_v\}$$

4. Edge set $E \leftarrow \{ e_i \mid i \in I_e\}$ forms an incidence matrix of size $I_v \times I_e$.
5. Constructed hypergraph displayed as $H = (X, E)$.

The human brain grows until its death. Means, the birth of new neuron will happen in the entire life cycle of a human being. So adding new neurons and locating its corresponding region is an important task shown in algorithm 2.

Either a single neuron or collection of the neuron was added in any of the already available edges or a new edge was created. During the development of neuron itself. There are many causes for the death of the neuron. Neurons die because of low energy levels, the wrong path, and collision with another neuron. To differentiate the information flow among the same and different regions of the brain, here, the communication of neurons among the same region was called a pathway and among different regions was called highway [33].

Algorithm 2 Adding Hyper-vertices and Hyper-edges

1. Input I_v and I_e
2. While (I_v = =0 and $I_e \geq 1$)
3. For each i and $i \in I_v$ do
4. Vector, $X \leftarrow \{x_i \mid x_i \neq \varnothing\}$
5. End for
6. For each i and $(i \in I_e) \wedge (e_i \subseteq X)$ do
7. Vector, $E \leftarrow \{ e_i \mid e_i \neq \varnothing\}$
8. End for

In algorithm 3, removing the vertex or the neurons without pathway was shown, which depicts the death of the neuron.

Algorithm 3 Deleting Hyper-vertices and Hyper-edges

1. Input I_v and I_e ;
2. If ($e_i > I_e$) then Stop
3. Else
4. For each I_e and $e_i \in E \in E$ do
5. remove vector, e_i ;
6. End for
7. For each I_v and $x_i \in X$ do
8. remove vector, x_i ;
9. End for

Hypergraph Coloring was implemented to differentiate the region of the brain. A transversal hypergraph was implemented for the information flow from one neuron to another along the pathway or highway. The flow chart in Fig 4 confers the view of the entire life cycle of the neuron. Mapping hypergraph for the model of a single neuron and multiple neuron construction is effortless. Since the hypergraph contains many nodes in a single edge. Hypergraph Framework models the life cycle of multi-level neuron construction. This framework will help the small lab neuroscientists to better understand and visualize the neuron developments and their behaviors.

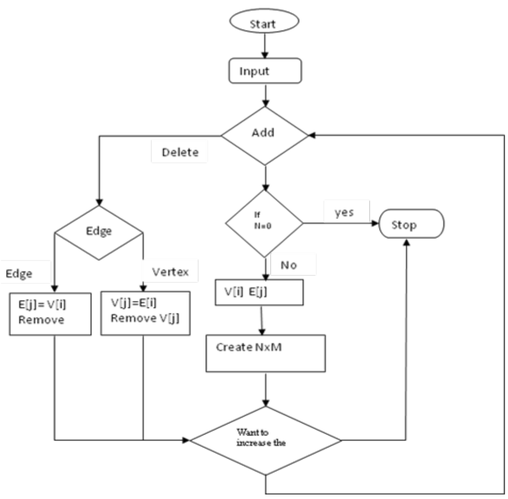

Fig.4. Shows the flow chart illustration for the construction process of hypergraph

4. Tools and Resources

The framework was implemented in C++ in a system configured with Windows 10 of Intel Core i7 CPU 3.40 GHz and NVidia GeForce GT 730 processor with 6GB RAM. The C++ code was executed in the GPU environment with CUDA. Latex tool was based on the idea of what you see is what you mean ('WYSIWYM'). It was also identified as an effective tool not only to create documents but also to create graphic elements. So, the visualization of the brain network was created in the Latex environment using the Tikz package [34]. The specialty of the hypergraph structure was already created using the tikz package, where multiple nodes are covered within a single edge. Drawing a hypergraph using Latex was not generalized. So in this paper, it was made generalized, based on user input and up to ~3,000 nodes and ~6000 communication paths of the huge network were applied.

5. Data Compilation

All elements of vertices and edges were loaded in the 'CSV' file. Initial value starting from one vertex and one edge was loaded to form an incidence matrix. Likewise, 16 input instances of different sizes of the matrix were created. Since vertex represents neuron and edge represent brain region. Each edge has information about the total number of the neuron and its connecting brain region.

6. Experimental Results

The neuron is one of the basic elements of the brain's nervous system. The brain starts with one neuron and grows up to 2, 50,000 neurons per minute in the early stage of brain development.

Forming a vector size of six hundred thousand per minute was very complex, so the idea was shown as a small sample. Table 1 provides information about the newly created and recreated matrix, mapped to the construction of the neuron and brain region.

Table1. Constructed neurons and brain regions.

Matrix	Number of vertices	Number of Edges	Number of each communication pathway
Original	8	6	28
Recreated	7	5	21

A sample of 8-neurons with 6 -corresponding brain regions and $\langle n \mid C \mid r \rangle = 28$ pathways were created and shown in Fig 5a. Similarly, the effect of the dead neuron was shown in Fig 5b using the incidence matrix. The hypergraph construction algorithm was used to decide whether a subject is normal or not. Let, n represent a neuron and m represent the brain regions. From the matrix, it has been inferred that n1 is the first neuron present in region r_5. Next neuron n_2 is present in region r_4 and r_5 and so on. Likewise, a full N x M matrix is formed, which represents a particular brain image of a normal person. The numeral '1' represents the presence of neurons, so the matrix was constructed with a hundred thousand neurons and displayed using the incidence matrix. During the old age, the normal subject will turn to abnormal due to the growth of human beings.

ni \ rj	r1	r2	r3	r4	r5	r6
n1	0	0	0	0	1	0
n2	0	0	0	1	1	0
n3	1	0	0	1	0	0
n4	1	0	0	0	0	0
n5	1	1	0	0	0	0
n6	0	0	1	0	0	0
n7	0	0	1	1	0	1
n8	0	1	1	0	0	0

Fig.5. a - Original Matrix

$ni \backslash rj$	$r1$	$r2$	$r3$	$r4$	$r5$
$n1$	0	0	0	0	1
$n2$	0	0	0	1	1
$n3$	1	0	0	1	0
$n4$	1	0	0	0	0
$n5$	1	1	0	0	0
$n6$	0	0	1	0	0
$n7$	0	1	1	0	0

Fig.5. b - Recreated Matrix

Fig.5. Hypergraph representation of brain image of a normal and abnormal subject

Consider neuron (n_7), it has three neurons in the region (r_3, r_4, r_6), when it becomes ideal for a long period of time, it was considered dead. That is the inactive numeral '1' will change to '0'. This leads to the region/the edge r_6 to become ideal. It signifies that dead neurons will cause the brain region to disappear from the normal view of a brain. That is called shrinkage. The shrinkage of the abnormal subject is shown in the recreated matrix. The addition of vertex and edge denoted the growth of the brain. The deletion of vertex or edges indicated the shrinkage of the brain. In this way, the framework identifies the abnormal subject with Alzheimer's disease [35]. It has been inferred that by viewing the hypergraph structure itself the physician will notify the abnormal changes in the brain region. The original matrix from Fig 5a represents the brain image of the normal subject. The recreated matrix from Fig 5b represents the reshaped brain image of abnormal Alzheimer's disease subjects [36]. From Fig. 5, two important information was inferred. Due to the death of neurons (n_7), first, the total number of communication pathways was shrunk.

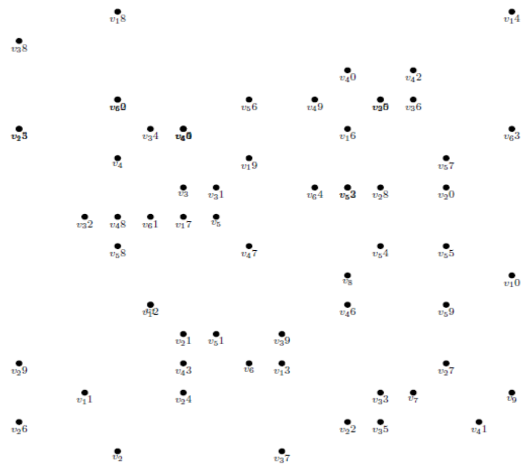

Fig.6. Shows a view of the huge collection vertex or neuron formed, here it has about 60 neurons.

Second, there was no communication highway between region (r_4) and (r_3). Also, it was inferred that the memory loss with Alzheimer's disease subject was happened due to this dead neuron and ideal region of the brain [37, 38].

The framework was able to form a huge cluster of vertex or neurons.

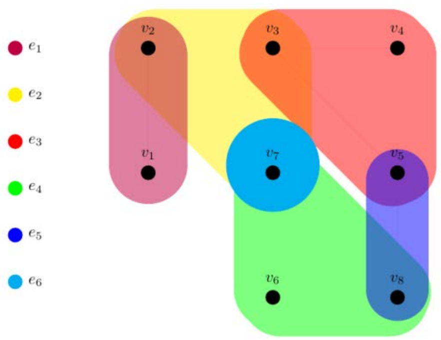

Fig.7. a

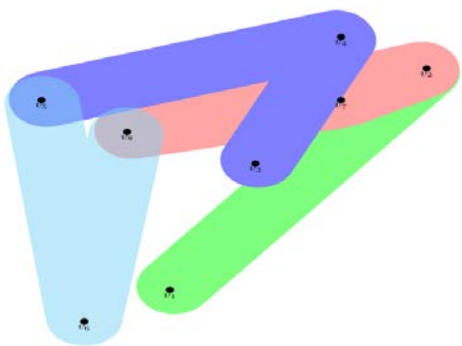

Fig.7. b

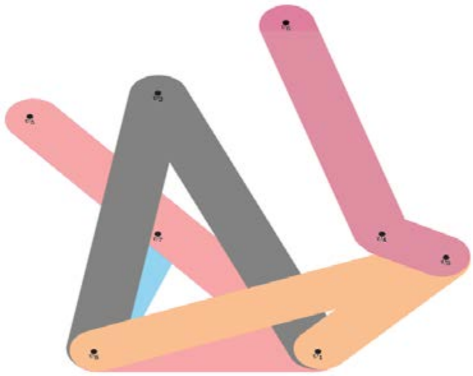

Fig.7. c

Fig.7. (a to c) Shows the visualization of hypergraph output using tikz package

It was shown in Fig. 6. It was used to check the closeness of the vertex or non-overlapping of the neuron. The specialty of the picture in Fig. 6 was about displaying multiple vertices into a single edge. Here, the edge was created automatically by the framework. Fig 7a shows the formation of 6 edges for 6 vertexes. Fig. 7b shows the different views of the same 6 vertexes but 4 edges. Fig 7c shows another view of the same 6 vertices with 5 edges. Overall, fig.7. (a-c) shows the visualization of a hypergraph and it signifies that there were many possibilities of placing the vertex or neuron in different locations of the brain. It will help the neuroscience researcher to study and analyze the different views of the same structure.

6.1. Performance Measures

The time complexity was measured for the construction of the hypergraph. It took O (n) and O (m) to create "m" edge and "n" vertices, respectively. It took O (n*m) to delete vertices and edges. Table 2 shows the sample instances and those tested against the model for time analysis. Even a complex graph with an N x M matrix size gives better execution time. Removing the rows and columns of the matrix takes less execution time compared to creation.

During run time analysis which is shown in Fig 8 and 9, it has been inferred that the loading and construction take more time than deleting the vertices and edges of the hypergraph. Loading a hypergraph indicates the incidence matrix creation, which involves both vertices and edges and form paths among them. Deleting the vertices and edges doesn't create a lot of change in the matrix.

Table 2. Input instances and its corresponding execution time.

No.	input	Create Vertex	Create Edge	Exe. Time	Delete vertex	Delete Edge	Exe. Time
1	8x6	8	6	10	3	1	2
2	35x40	35	40	25	12	3	6
3	60x40	60	40	53	12	12	8
4	60x60	60	60	74	24	12	12
5	120x100	120	100	84	32	12	12
6	200x180	200	180	88	50	30	24
7	250x240	250	240	120	100	50	26

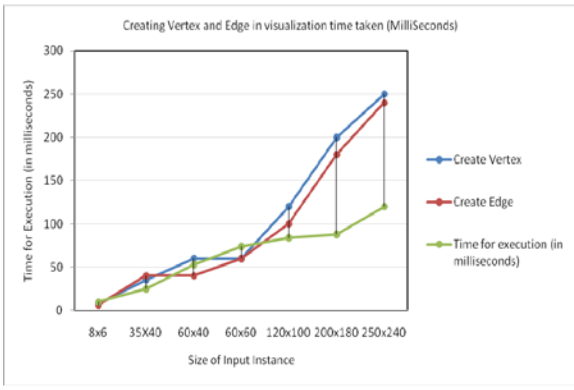

Fig.8. Shows the runtime analysis for the construction of nodes and edges.

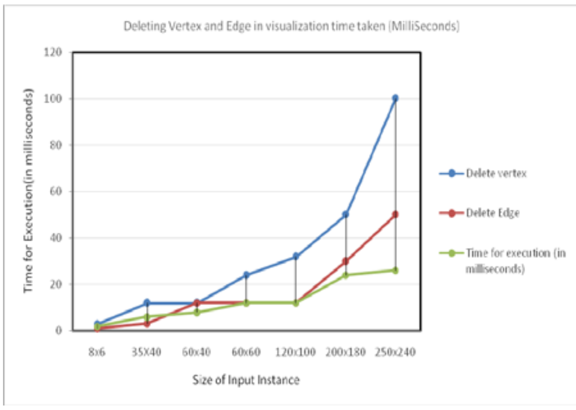

Fig.9. Shows the runtime analysis for the reconstruction of nodes and edges.

The correctness of the hypergraph creation in the visual environment was assessed quantitatively by means of the following two measures namely Small-World Network [39] and Robust Connectivity Measures [40]. Small-World Network provides the structural properties of neighbors and non-neighbors of hypergraph through the measure of $L \infty LogN$. Robust connectivity measures of the graph are also feasible [41].

6.2. Applications

Graph theory methods applied to the brain provide powerful innovative insights into the structure and function of networked brain systems. Graphs were best suited to show the statistics of network evolution, architecture and developments. Generative models from deep learning help to understand the dynamics of the brain network. Normal graph theory was composed of dyadic interactions. Higher-order interactive network like hypergraph will help to analyze non-random attributes of the brain network.

7. Conclusion and Future Work

Neuron architecture was applied in graph theory and visualized in C++ with the Latex environment. The birth and death of the nerve cell were realized through the construction and reconstruction operation of the hypergraph. This proposed hypergraph-based neuron reconstruction framework to understand the life cycle of neurons will help the neuroscientists to better understand and visualize the development of neurons and their behaviors. The structural changes during brain disorder were also identified among human brain images. In future work, this hypergraph-based neuron model framework will be updated as the MRS Framework. MRS defines Suitable Reconstruction Models for brain image analysis. This framework will also operate as a treatment modality in small labs to cure brain diseases and disorders that affect the lives of millions of human beings.

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