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Design of Virtual BrainUsing IOT

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Abstract—Virtual brain research is ramping up the development of low-cost real-time brain-computer interfaces (BCI). Hardware advancements that improve the capabilities of Virtual brain analysers and Brain Computer wearable sensors have enabled the development of various new software frameworks for developers to leverage and construct applications integrating BCI with IoT. It also offers various sensory channels for larger-sized data transmissions to users' brains. The intersections of these two research lines are advancing both sectors and will drive the requirement for an energy-aware infrastructure to serve the mobile cloud's broader local bandwidth demands. In this study, we conduct a survey of BCI in IoT from several viewpoints, including EEG-based BCI models, machine learning, and current active platforms. Based on our research, the key findings of this study emphasise three important BCI development trends: EEG, IoT, and cloud computing.

Keywords—EEG, IOT, Virtual Brain, Cloud Computing.

I. INTRODUCTION

The capacity to map the human brain at multiple sizes with better throughput and resolution is at the top of the list of the US Government's BRAIN Initiative. A full depiction of the brain anatomy will reveal fresh insights into how the human brain works and may aid in the development of novel therapies and drugs for brain illnesses. Recent advancements in intact brain imaging, such as the CLARITY and MAP (Magnified Analysis of the Proteome) tissue clearing procedures, allow for the collection of huge volumetric pictures of brain tissue at cellular and subcellular levels[3]

However, the tremendous volume and resolution of brain images presents a difficulty for effective processing and interpretation. We created an automated dense axonal fibber tracing process that can track long-distance fibbers and build 3D connection maps that contain not only the vertices and edges of a network graph, but also the 3D position information associated with each fiber's track. In addition to standard graph analysis, we are interested in discovering long-distance neuron fibre connections and fibre crossings, both of which might show interesting patterns when evaluated at cellular resolution and at a long distance (1 mm). Brain graphs provide a framework for representing structural or functional topology at several levels. There are several software tools available for analysing the topology of brain networks utilising graphs[4].

The Apache Accumulate database is based on Google's Big Table database and enables for quick ingestion and extraction as well as the storage of enormous amounts of data. The Dynamic Distributed Dimensional Data Model (D4M) is a mathematical framework based on associative array mathematics that has been used to a variety of disciplines including cyber security, biology, free text, and social media data. D4M may also be utilised within a database to execute linear algebraic calculations.D4M integrates easily with the pMatlab parallel computing environment, which enables MATLAB/Octave programmers to employ a single-program-multiple-data (SPMD) parallel programming approach. PMatlab is a message passing interface library that has been used for a number of parallel applications[1].

Synchronized activity appears to offer functional connections, both locally and between distant brain areas. Thus, brain networks are made up of physically dispersed but functionally coupled information-processing areas. Brain connection analysis is based on three distinct but related types of connectivity. (i)Anatomical connection (AC), also known as structural connectivity, is a type of connective formed by synaptic interactions between neighbouring neurons or fibre trackslinking neuron pools in geographically distant brain areas. White matter refers to the whole set of such fibber tracks in the brain. Anatomical connections are extremely enduring and robust on short time scales (sec, min), although significant plasticity can be detected over longer time spans. (ii)Functional connectivity (FC), defined as the temporal dependence of neuronal activity patterns from physically distinct brain areas[2].

These network topologies represent two fundamental concepts underpinning brain information processing: functional segregation and functional integration. Neuroimaging techniques (EEG, MEG, fMRI, PET, and SPECT) and neuroanatomical approaches provide the majority of the experimental evidence supporting such network topologies. Signal transmission across different brain areas necessitates connecting fibre tracts, which provide the structural foundation of the human connective.

As a result, 3D-PLI enables an independent review of DTI data. Brain connection may be measured by encoding neighbourhood relationships into a connectivity matrix, the rows and columns of which correspond to distinct brain areas[5].

This form lends itself to mapping to a graphical model, which allows for the quantification of many topological properties of the connectome. Graphical models provide a flexible mathematical framework for studying pairwise relationships between interacting brain areas in general. In recent years, there has been an exponential development in

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the number of papers relating to the use of graph theory to uncover structural, functional, and effective connection aspects from neuroimaging investigations[6].

This is not meant to be exhaustive, but rather to highlight some common works in this topic.

Following that, various interesting applications and contemporary computational approaches dealing with functional connectivity are gathered. This is followed by a brief review of recent research on effective connectedness. Finally, the critical notion of graphical models applied to such complicated brain networks is presented, as well as potential applications to connection analysis[7].

II. Literature Survey

T. R. Insel et.al., discussed about the BRAIN Initiative, which aims to create breakthrough technologies to investigate how the brain's cells and circuits interact at the speed of thinking and, ultimately, to uncover the intricate relationships between brain function and behaviour. The problems are unique because brain architecture ranges from the size of chemical interactions at trillions of synapses to the billions of cell bodies that join to build local networks that subsequently integrate across different brain regions. There are temporal scales in addition to spatial scales since brain circuits are not static but constantly alter as a result of neuronal activity, developmental stage, and ageing.

K. Chung et al. explained how hydrogel-based structures may now be formed from within biological tissue to allow future removal of lipids without mechanical disassembly of the tissue. This method results in a tissue-hydrogel hybrid that is physically stable, retains fine structure, proteins, and nucleic acids, and is permeable to both visible-spectrum photons and foreign macromolecules. Here, we emphasise the approach's significant limitations and prospects, particularly in terms of integration with other approaches for brain-mapping investigations.

J. Swaneyet.al., discussed about magnified analysis of the proteome (MAP), which linearly extends whole organs fourfold while maintaining their general architecture and three-dimensional proteome structure. The concept of MAP is based on the finding that limiting crosslinking between and between endogenous proteins during hydrogel-tissue hybridization allows for spontaneous expansion following protein denaturation and dissociation. The protein composition, tiny subcellular features, and organ-scale intercellular connections are all preserved in the enlarged tissue. We employ commercial antibodies for repeated rounds of immunological labelling and imaging of a tissue's enlarged proteome, and our results show an 82 percent success rate (100/122 antibodies tested). We showthat in the mouse brain, specimen size may be reversibly changed to scan both inter-regional connections and precise synaptic topologies.

S. M. Smith et.al.discussed aboutto evaluate alternative connectivity estimate methodologies, FMRI data for a wide range of underlying networks, experimental protocols, and problematic confounds in the data were collected. Our findings demonstrate that correlation-based approaches may be highly successful in general, methods based on higher-order statistics are less sensitive, and lag-based approaches perform extremely badly. More specifically, several methods, including partial correlation, regularised inverse covariance estimation, and several Bayes net methods, can provide high sensitivity to network connection detection on good quality FMRI data; however, accurate estimation of connection directionality is more difficult to achieve, though Patel's can be reasonably successful.

III. System Analysis

A. *Existing Method*

- In terms of identifying brain activity, BCIs are currently pretty incorrect.
- Outside-of-the-head BCIs have limited ability to interpret brain impulses.
- They can be implanted under the skull, but this involves major surgery.
- Reading people's inner thoughts raises a slew of ethical concerns.

B. *Proposed Method*

A full depiction of the brain anatomy will reveal fresh insights into how the human brain works and may aid in the development of novel therapies and drugs for brain illnesses.

➢ We examine extant BCI VR research from three critical perspectives: EEG-based BCI models, machine learning, and platforms. The findings can be utilised as a starting point for future relevant study.

IV. System Requirements

Hardware Requirements

➢ EEG Electrodes
➢ Signal conditioning
➢ Amplifier
➢ TFT controller
➢ PC 2.5

Software Requirements

➢ MPLAB IDE
➢ Embedded C Language
➢ Hi-Tech Complier

V. Working Modules

➢ Sensors Architecture

➢ Serial Communication System & Sensor Monitoring

➢ Sending Mail & Storage

A. *Sensor Architecture*

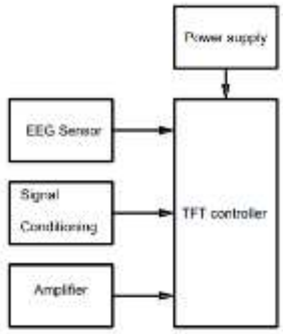

Fig. 1. System Architecture

- The power supply provides total power to the sensors and TFT controller.
- An electroencephalogram (EEG) is a test that measures electrical activity in the brain.
- Electrical impulses allow brain cells to communicate with one another. An EEG can be used to detect possible issues connected with this activity. Signal conditioning is a data collecting procedure that uses an equipment called a signal conditioner.

B. *Serial Communication System & Sensor Monitoring*

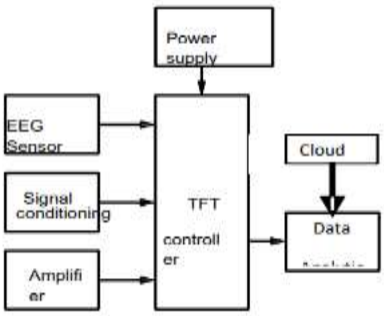

Fig. 2. Block Diagram

- Communication between Data Analytical and Cloud occurs in this Module.
- A healthcare unit would need to invest considerably in infrastructure and maintenance resources if the cloud performed all functions related to storage, data modification, transfer, and collaboration internally.
- Analytics makes it possible to evaluate vast amounts of healthcare data gathered on a daily basis and get important insights into problems that would otherwise be difficult to foresee. In fact, doctors will soon use analytics to learn the full history of their patients.

C. *Sending Mail & Storage*

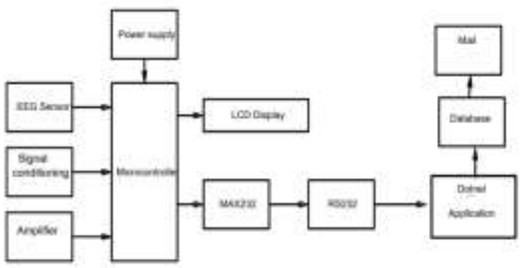

Fig. 3. IOT

- The computer has a database and a Dot Net application.
- The Database is where the sensor values from the microcontroller are saved.
- The sensor values are sent to the specified email address via the dot net application.

VI. METHODOLOGY

A real-time web-based 3D user interface that queries data from accumulating and flat files displays the fibre traces.

A. *Technologies and Platform Design*

1) Imaging Pipeline: The first step of the pipeline is to divide the original large data into sub volumes and apply image processing algorithms in parallel using pMatlab. The main image processing algorithms include a convolutional neural network (CNN) for segmenting the axon fibers, and a number of morphological operations for extracting fiber tracks, from which a network graph of vertices, edges, and 3D coordinates of the fiber tracks are computed. Our CNN has three convolutional and two fully connected layers. The last layer uses sigmoid activation, and all other layers use rectified linear units (ReLU) . In the graphs, vertices correspond to the start/end of the fiber tracks and edges represent the connections (fiber tracks) between the vertices. These parsed graphs are then converted into an associative array format, which is amenable for graph analysis.

2) Accumulate and D4M: After converting the graphs to an associative array format, they may be placed into accumulate or saved to flat files. Based on our benchtop testing, we discovered that a hybrid strategy that uses both the accumulation database and the file system provides the best performance. The fibre graph vertices and edges are saved in accumulate, whereas the fibre track 3D coordinates are saved in flat files. When opposed to vertices and edges, 3D coordinates are much denser data and would significantly slow down retrieval time if kept in accumulate. Furthermore, because 3D coordinates are primarily employed for morphological analysis and visualisation, they are not as often accessible as vertices and edges.

3) Binary tree encoding based on geohashing for sub volume indexing: Gustavo Niemeyer devised the geohash, which is a geocoding method based on a hierarchical spatial data structure that subdivides space into an easily identifiable grid. The structure of geohashed data provides two advantages when utilised in a database. First, geohash data will comprise all of the points for a specific rectangular region in continuous slices.

4) Data Schema: In the following form, nodes are graph vertices and links are edges that connect nodes in the network. The node ID is the node's locally unique number in each sub volume. The binary code where the node is placed is represented by the sub volume number. End Yes is either 0 or 1 depending on whether the node is an end node, with 1 indicating the beginning

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or end of a fibre track and 0 indicating a junction that links to numerous additional nodes. End Node is the node ID of the other nodes to which this node is linked. Links refers to the link IDs of the links that connect to this node.

VII. Algorithm

The BFS method traverses a network data structure to locate vertices that are related to one another. BFS intuitively informs us which neurons are related to other neurons in our application. Using the previously mentioned associative array structure, we can immediately apply BFS to a node (or collection of nodes) by multiplying two associative arrays. To apply BFS to a node, we must first extract the sub volume of interest from accumulate in order to generate an incidence matrix E. The required node is then added to an associative array and multiplied by the incidence matrix of the relevant subgraph of the sub volume.

As a consequence, an associative array with information about the nodes related to the input nodes is created.

The desired node link information is then extracted. This method can be done indefinitely to locate all nodes linked to the resulting.

VIII.SIMULATION RESULTS

Fig.4. Status Page

Fig.5. Login Page

This is an example of php server page development for IoT.

Here I built by providing a location for the formation of our virtual storing of data in memory, which will be preserved indefinitely until the owner of the virtual brain maker edits or deletes the page source.

It also has the opportunity to enter and save email addresses for recipients.

A. Hardware Results

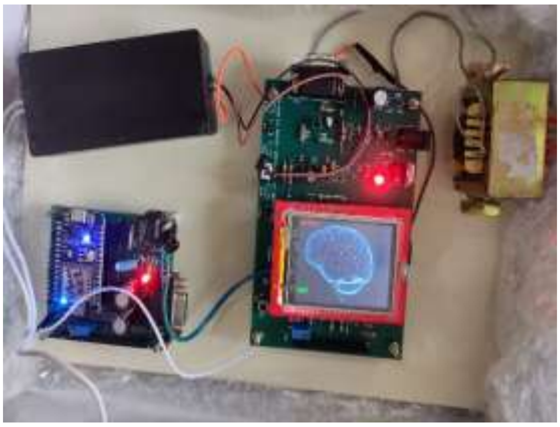

Fig.6.Normal State of Brain

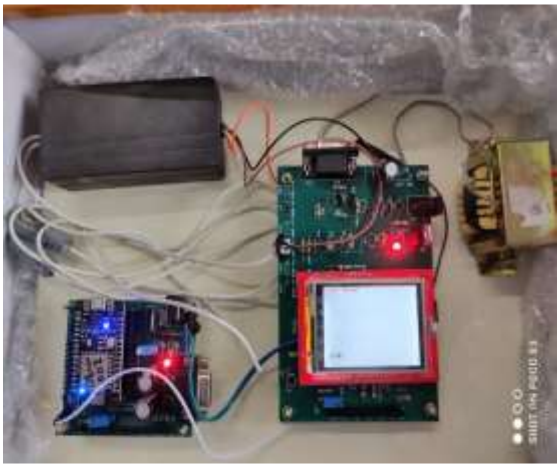

Fig.7.State of brain dead

IX.CONCLUSION

Using Apache Accumulate and D4M, we developed a cloud-based solution for undertaking large-scale brain connection analyses. We proved that our method can perform quick data querying and extraction for graph analytics and visualisation. With geo hashing-based binary tree encoding, which provides a Google Maps-like viewer with numerous zoom levels, indexing of sub volumes is straightforward and logical. There are several opportunities for future employment. First and foremost, we want to improve the online GUI by making it more interactive and user pleasant.

Furthermore, we want to scale it to analyse considerably bigger datasets (terabytes and higher), with the eventual objective of doing such analysis on the human brain. We're looking on using Graphology to perform graph analytics directly into accumulate.

We are also investigating the usage of a poly storage database, such as Big DAWG, as a data viewer that displays the original data as well as a zoomed-in view of four nearby sub volumes extracted using a management solution that closely aligns data sources with data management technologies.

At collecting data from sensors and updating it on the hospital's main server. As a result, this procedure proceeds

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regardless of whether the doctor or a patient's relative is there beside the patient. By examining the patient's health, the doctor can advise the patient on any therapy. This project will use IOT technology to simplify the medical evaluation procedure, allowing the patient to enjoy a carefree life.

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