Fog Computing Assisted Anaesthesia Monitoring to Enhance Realtime Surgical Efficiency.

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Published version

FERNANDES, Caren, ZASADA-JAMES, Jonathan, ADHIKARI,, Kavya, UL HASAN, Najam, BALDWIN, James and HIRSCH, Laurence (2024). Fog Computing Assisted Anaesthesia Monitoring to Enhance Realtime Surgical Efficiency. In: 2024 International Symposium on Sensing and Instrumentation in 5G and IoT Era (ISSI). IEEE. [Book Section]

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Abstract— **Anaesthesia plays a crucial role in modern surgical procedures, ensuring patient comfort and allowing surgeons to perform necessary interventions without interruptions. However, managing anaesthesia comes with significant challenges, such as avoiding underdosage or overdosage, which can lead to severe complications like intraoperative awareness or cardiovascular instability. This paper proposes a fog computing-based approach to improve real-time anaesthesia monitoring, leveraging IoT nodes armed with EEG tools for continuous updates on the patient's brain activity and eventually translating into anaesthetic depth. By strategically deploying fog nodes and offloading task distribution from IoT nodes to fog nodes as well as cloud services, the proposed system aims to reduce response time for performing complex computations on brain activity signals, thereby increasing the workflow efficiency of anesthesiologists. To achieve this, a dashboard using a web platform is developed to provide anesthesiologists with a comprehensive interface for real-time monitoring and control, which will help anesthetists predict anaesthetic depth and make informed decisions. By improving the accuracy and timeliness of anaesthesia management, the proposed approach not only enhances patient safety but also optimises the operational efficiency of surgical procedures.**

Keywords—Internet of things, fog computing, cloud computing, Anesthesia

I. INTRODUCTION

Anaesthesia is an essential component of modern surgical procedures, enabling the safe and effective execution of operations that would otherwise be impossible while the patient is awake. By keeping the patient unconscious and free from pain, anesthesia ensures their comfort and allows the surgeon to perform the necessary interventions without interruption. However, the administration of anesthesia comes with its own set of challenges. Both underdosage and overdosage can result in serious complications, such as the patient regaining consciousness during surgery (intraoperative awareness), breathing difficulties, and cardiovascular instability. Anaesthesiologists have the responsibility of closely monitoring the patient's vital signs and adjusting the level of anesthesia to maintain appropriate sedation throughout the entire procedure [1].

The emergence of the Internet of Things (IoT) has provided an opportunity to improve patient safety, surgical outcomes, and the workflow efficiency of anaesthesiologists during procedures. IoT sensors can be seamlessly integrated with monitoring devices to gather immediate data on vital signs, including heart rate, blood pressure, oxygen saturation, and respiratory rate. Advanced Electroencephalogram (EEG) tools can also be employed to monitor brain activity in real-time, aiding in the evaluation of anesthetic depth and the detection of potential risks like awareness or over-sedation [2,3]. These technologies offer continuous updates on the patient's consciousness level and anaesthetic depth, empowering the anaesthesiologists to make prompt adjustments to the anaesthesia administration.

To address the low-latency requirements of anaesthesia monitoring, this study proposes a fog computing-based approach. Fog computing extends cloud computing capabilities to the edge of the network, closer to the data source, thereby reducing latency and enhancing real-time data processing capabilities [4]. Basic processing and analysis of vital sign data, such as calculating averages, identifying sudden changes, and exceeding predefined thresholds, can be performed on fog nodes. This enables near-instantaneous (less than a second) responses to the anaesthesiologists. Initial processing of EEG data, like filtering noise and extracting relevant features, can also be done on fog nodes, reducing the amount of data that needs to be sent to the cloud for further analysis and improving overall processing speed (with less than a second delay) [2].

Based on data that is processed by the fog nodes, the client node on the edge layer can trigger immediate alerts for critical situations, ensuring that anesthesiologists are promptly informed of any anomalies that require intervention. When multiple fog nodes are available, the system can offload tasks to this cluster of fog nodes to enhance real-time processing and decision support. This approach avoids overloading individual nodes and ensures the timely completion of critical tasks, as the workload can be distributed across the fog network based on factors such as processing capabilities, current workload, and proximity to the data source [5].

To enhance the usability of the proposed system, the conceptualised underlying infrastructure manages the vital EEG data from creation through instant alert generation and delivery to anesthesiologists, culminating in storage and archival. The system incorporates two physical and one virtual layer to oversee this end-to-end. Key lifecycle stages—creation, collection, streaming, cleaning, processing, and analysis—are distributed across the three infrastructure layers.

The edge layer, also known as the initiation layer, exists in the patient's immediate surgical environment. Devices on this layer primarily focus on creating, collecting, and streaming data from EEG sensors placed on the patient's head to downstream system layers. Leveraging its proximity to the patient, this layer must be ideally suited to host a dashboard displaying the mean power spectral density (PSD) values for different EEG frequency bands derived from the processed data provided by the second layer. This dashboard quantifies the patient's consciousness level, enabling anesthesiologists to effectively monitor EEG readings in real time during surgery.

The intermediate fog layer is the critical hub between the upstream edge and downstream cloud layers. This layer hosts a network of IoT devices called fog nodes dedicated to the core functions of cleaning and processing the incoming EEG data stream into the desired output. The layer's output is bi-directional, designed to send data both upstream for immediate alert generation and downstream for in-depth analytics and long-term storage.

The cloud-based ecosystem is the final downstream layer that incorporates a suite of services dedicated to storing and analyzing processed data. A cloud-based dashboard presents the patient's state, inferred from anesthesia depth indicators derived from the mean power spectral density (PSD) values across various frequency bands processed by the preceding layer.

Progressive iterations of enhancing the cloud layer could accommodate advanced analytics, comprehensive patient data, and a customizable user interface. This could enable the dashboard to proactively identify potential awareness or overdosage through trend analysis and anomaly detection, triggering real-time alerts. It could also provide access to detailed patient information, including medical history, and system performance metrics such as fog node status, processing load, and task distribution. To enhance user experience, the dashboard could empower anesthesiologists to personalize its layout and prioritize displayed information based on individual preferences and specific surgical requirements.

To evaluate the performance of the proposed system, the end-to-end latency should be measured, and the processing and memory utilisation of fog nodes should be monitored to ensure there is sufficient capacity to handle the computational demands of real-time anesthesia monitoring without overloading. Metrics such as response time and residual capacity of the fog nodes should be assessed to validate the effectiveness of the fog computing approach in enhancing real-time monitoring and decision support during surgical procedures.

This work presents a novel fog computing-based approach for real-time anesthesia monitoring in hospitals, leveraging the capabilities of IoT and fog computing to enhance patient safety, surgical outcomes, and the workflow of anesthesiologists. By strategically deploying fog nodes and offloading tasks to a network of fog nodes, the proposed system aims to provide near-instant processing and critical decision-support capabilities to anesthesiologists, ultimately contributing to the improved management of anesthesia during surgical procedures. The integration of IoT, advanced data analytics, and fog computing represents a significant advancement in the field of anesthesia monitoring, offering a robust and scalable solution for enhancing patient care in modern surgical environments.

The rest of the paper is organised as follows: Section II discusses the system architecture. Section III covers the experimental setup, presents the results obtained, and includes a discussion of these results. Finally, Section IV concludes the paper and outlines directions for future work.

II. System architecture

The system architecture for this work can be divided into three main layers: the Edge Layer, the Fog Layer, and the Cloud Layer, as depicted in Fig. 1.

A. Edge Layer: The edge network features an OpenBCI UltraCortex Headset for continuous EEG data acquisition to continuously monitor the patient's brain activity through EEG signals [6]. This low-cost, open-source brain-computer interface mounted with an OpenBCI Cyton Biosensing Board allows real-time acquisition of EEG data. Eight channels of EEG data are collected from the headset's sensors/electrodes by the Cyton Board and transmitted wirelessly to a Raspberry Pi within the same edge network. A dedicated USB dongle connects the Raspberry Pi to the Cyton board, enabling the continuous
load balancer. The 'Client Pi' utilises Python with Brainflow library to stream data from all 8 channels of the Cyton board and push it to the intermediate fog layer.

B. Fog Layer: At the heart of the system, the fog layer plays a crucial role in the system architecture, with strategically placed clusters of fog nodes handling the next stage of data processing [8]. For this purpose, a cluster of eight Raspberry Pi 4 nodes has been formed to constitute a fog network, termed 'Octapi'. The Octapi, in conjunction with the 'Client Pi' (Raspberry Pi 4) from the edge layer, performs functions such as data reduction. This data reduction technique involves processes like downsampling, filtering, and feature extraction to condense the raw EEG data into a more compact and efficient format. This data reduction ensures that the processed information is efficiently forwarded to the nearest fog node for further analysis, reducing the overall data load and improving the system's responsiveness [7].

First, the Octapi receives the different tasks requiring execution. Subsequently, the 'Client Pi' assumes the role of coordinator, executing a scheduling or assignment algorithm to distribute these tasks among the server Raspberry Pi 4s within the cluster. Both the 'Client Pi' on the edge layer and the Octapi on the fog layer are equipped with a common processor, Dispy [9], which handles workload distribution for incoming EEG data processing.

Dispy on the 'Client Pi' intelligently identifies suitable fog nodes and offloads raw EEG data to them for further processing. Upon receiving data, fog nodes employ advanced signal processing techniques to transform signals from the time domain into the frequency domain. This conversion enables fog nodes to transfer EEG data from the patient during surgery. The Raspberry Pi 4 designated as the 'Client Pi' functions as a central hub, receiving raw EEG data from the OpenBCI device and operating as both a client server and extract crucial EEG data features, such as power spectral density and power levels within specific frequency bands (e.g., alpha, beta, gamma) [10].

Upon completion, the server interface of Dispy on fog nodes directs output to the interconnected upstream edge and downstream cloud layers. The Client Pi interface serves as a receiver of processed data on the upstream edge layer. The resulting responses and changes in PSD band features offer valuable insights into the patient's brain activity and anesthetic depth, enabling

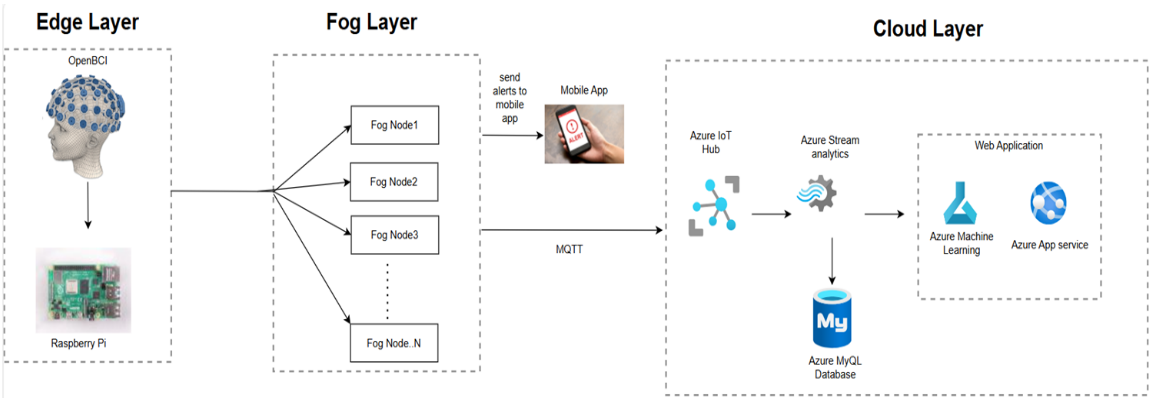

Fig. 1. System Architecture for the Developed System

anesthesiologists to closely monitor patient status and respond accordingly [6].

A noticeable change in PSD band, based on defined thresholds, triggers an immediate automatic alert to anesthesiologists. To facilitate timely decision-making by anesthesiologists, a mobile app with a dashboard has been developed to disseminate these instant alerts. Additionally, fog nodes conduct advanced event detection on the EEG data. By employing sophisticated algorithms, they identify unusual patterns or spikes indicative of potential patient issues.

C. Cloud Layer: Upon receiving processed data from fog nodes, the cloud layer prepares it for subsequent analysis and long-term storage. Initially, Azure IoT Hub ingests the processed data streams from fog nodes. Subsequently, Azure Stream Analytics forwards the stream to Blob storage. Fuzzy logic is then applied to the data residing in a dedicated container in Azure Blob Storage to predict the patient's state with reasonable accuracy. The results of this analysis are then stored as JSON files in a second container on Azure Blob Storage for historical record-keeping and future reference. A cloud-deployed web application visualizes this predicted patient state for broader analytics. Additionally, the cloud application offers the capability to download prediction reports. This enables easy retrieval and analysis of the data over an extended period, allowing clinicians and researchers to study the patient's condition, identify trends, and potentially improve anesthetic management protocols [7,8].

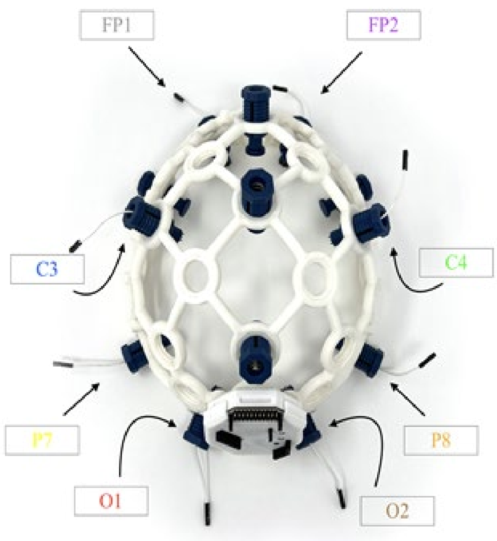

Fig. 2. UltraCortex Headset

The integration of Edge, Fog, and Cloud layers within this system architecture is engineered to optimise response times, ensure patient safety, and streamline the workflow efficiency for anesthesiologists. By employing a strategic distribution of data processing and analytics across these layers, the architecture enables real-time monitoring, rapid alert generation, and seamless workflow integration. Real-time monitoring ensures continuous observation of patient data with minimal latency, while rapid alert generation allows for immediate detection and notification of critical events based on predefined thresholds and machine learning models. Seamless workflow integration harmonises data flow and analysis with existing healthcare systems and practices. This layered approach ensures that data is processed at the most appropriate level—Edge for immediate, local processing; Fog for intermediate, near-real-time analysis; and Cloud for comprehensive, long-term storage and advanced analytics. Consequently, the system enhances clinical decision-making and operational efficiency, ultimately improving patient outcomes and surgical procedure effectiveness [11].

III. RESULTS AND DISCUSSION

To obtain the results, the first step involves capturing the patient's brain activity. This is achieved using an 8-channel UltraCortex Headset in conjunction with a Cyton Board, both integrated with the OpenBCI GUI [6]. Designed for high comfort and stability, the UltraCortex Headset ensures consistent electrode contact with the scalp for accurate EEG signal acquisition. The Cyton Board, equipped with 8 channels, interfaces with the headset to receive and transmit EEG signals. Each channel corresponds to a specific electrode, and the signals from these channels are visualized in the OpenBCI GUI. This versatile software seamlessly integrates with the hardware, displaying each channel's signal in a distinct color matching the headset's wiring. The OpenBCI GUI was initially used during setup solely to verify data comprehension and testing.

The UltraCortex Headset, as depicted in Fig. 2, is carefully positioned on the patient's head to accurately capture brain activity during surgery. The Cyton Board's 8 channels record EEG signals from multiple scalp locations, providing a comprehensive overview of brain function.

The raw EEG data from all 8 channels is presented in Fig. 3. This data serves as the foundation for subsequent processing and analysis on fog nodes and the cloud infrastructure, enabling real-time monitoring.

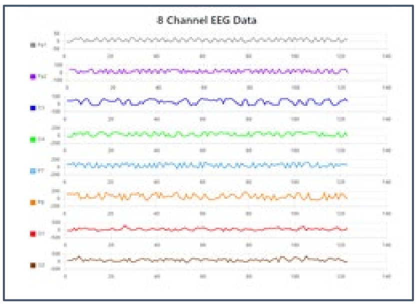

Fig. 3. EEG Data Received from UltraCortex Headset via Cyton Board.

The meticulous placement of the UltraCortex Headset, combined with the Cyton Board's 8 channels and the Client Pi, enables the system to capture a comprehensive and accurate representation of the patient's brain activity. This facilitates efficient management of anesthesia administration during surgery through a fog computing-based approach.

The edge layer's Client Pi (Raspberry Pi 4) employs Python and the Brainflow library to stream EEG data from the Cyton Board's 8 channels at a 250 samples per second rate. This data is then forwarded to a cluster of fog nodes. By capturing high-quality EEG data in real-time and efficiently streaming it, the system ensures optimal preparation for subsequent analysis within the fog and cloud layers.

Following data collection and storage, the Client Pi offloads data to an available fog node within the Octapi cluster using the Dispy middleware. At this stage, initial preprocessing, including bandpass filtering and Fast Fourier Transform (FFT) to generate the Power Spectral Density (PSD), is performed. These steps are visualized in Figure 4.

First, the raw EEG data sent to a Fog node is then passed through a bandpass filter (1-50 Hz) to remove low-frequency drift and high-frequency noise. The result of the bandpass filtering is shown in Fig. 4a.

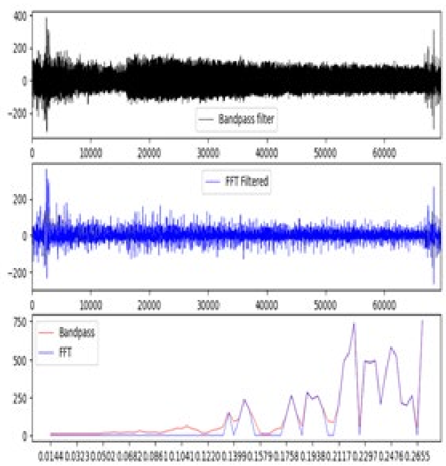

Fig. 4. (a) EEG bandpass filtered data (b) FFT of EEG data, (c) PSD of EEG Data

Next, the Fast Fourier Transform (FFT) is applied to the denoised data. This process identifies and retains the significant frequency components based on a Power Spectral Density (PSD) threshold,

effectively reducing noise by zeroing out the insignificant frequencies. The data after the FFT processing is shown in Fig. 4b.
Finally, the PSD of both the bandpass-filtered data and the FFT-processed data is computed and depicted in Fig. 4c. This visualisation provides insights into the frequency components of the preprocessed EEG signals, enabling further analysis and interpretation.

Once the PSD data is computed, it is decomposed into five frequency bands to assess the anesthesia level: Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz), Beta (13-30 Hz), and Gamma (30-50 Hz). To demonstrate this, a 5-minute sample EEG recording was taken, the PSD was computed after FFT, and then the mean power in each of the aforementioned frequency bands was calculated, as shown in Fig. 5.

This bar chart visualises the normalised mean value of each power band. The normalisation process scales the power band data values to a range of 0-100, which allows for easier comparison between different frequency bands.

Interpreting the PSD allows for the assessment of whether the anesthesia level is an underdose or overdose. Spikes in the bands' activity highlight the 'prominent power band' at that time. Based on this analysis, the anesthesia level can be determined, and recommendations can be sent to the anesthesiologists. Additionally, this data can be sent to the cloud for further in-depth analysis using machine learning algorithms to enhance decision accuracy and improve overall outcomes.

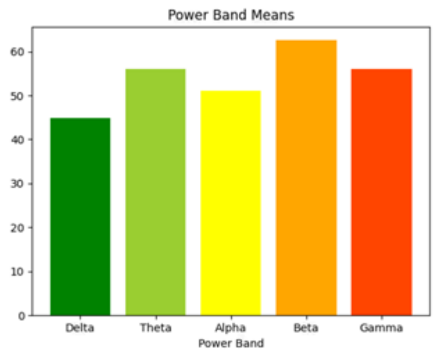

Fig. 5. Mean values of power bands

To provide anaesthesiologists with timely critical alerts derived from fog-processed edge data, a subscription-based mobile notification application was developed using the cross-platform Cordova framework. Upon installation, anaesthesiologists can subscribe to notifications, generating a Firebase Cloud Messaging (FCM) registration ID for their device. This ID facilitates targeted alert delivery.

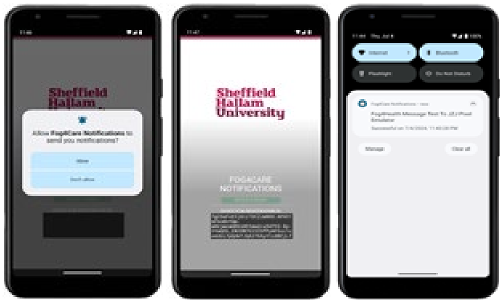

Fig 6. Snapshot of developed mobile application

In essence, Edge-collected EEG data undergoes advanced signal processing and real-time analysis within the fog layer. Processed data is then streamed back to the edge for critical event detection. Upon identification of significant changes, the edge triggers alerts, which are promptly delivered to the mobile app via Firebase Cloud Messaging (FCM). ensuring the anaesthesiologist's device receives these notifications even if the app is closed or inactive. Fig. 6 shows the snapshot of the developed mobile application.
Fog nodes forward processed data to the cloud layer, where a React and Python-based web application shown in Fig.7 and Fig.8 aggregates and extrapolates information to predict the patient's near real-time brain state.

Fig 7. Snapshot of cloud-based web application

Fig 8. Snapshot of cloud-based visualisation

Real-time communication is achieved using a Channels library with WebSocket protocol and Azure Redis Server. The Django web app processes data sourced from an Azure Blob storage container ('fog4care') using fuzzy logic for state prediction. Processed data is visualised on the dashboard shown in Fig.9 and stored in another Blob storage container ('processed_data') in JSON format. For detailed analysis, users can download data as CSV files, including state, duration, start, and end times.

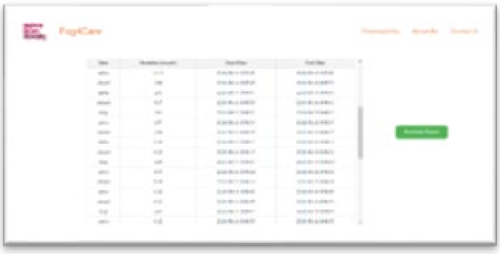

Fig 9. Snapshot of cloud-based report

A comparative analysis was conducted to verify if the Fog layer meets the low latency expectation of the fog computing approach. To establish a comparison, fog layer processing was replicated on the cloud layer using an Azure Function as depicted in Figure 11.

Fig 11. Snapshot of cloud Azure Function

The comparison was to measure the latency of processing a 30-second EEG data stream. Fig 12 shows how local Fog cluster has lower latency than the cloud.

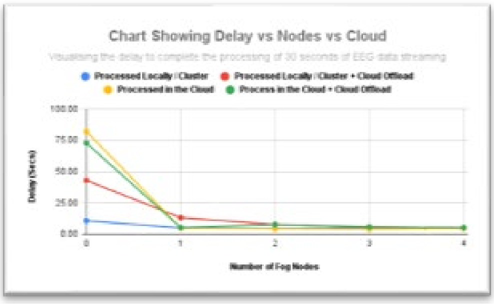

Fig 12. Snapshot of fog and cloud comparison for latency

CONCLUSION and FUTURE WORK

This work presents a fog computing-based approach for real-time anesthesia monitoring in hospitals. The system utilises IoT nodes armed with EEG tools to continuously monitor patients' brain activity, which is then mapped to gauge the anesthetic depth of the patient, whether the patient is underdosed or overdosed. The fog layer optimises latency and real-time responsiveness through advanced signal processing and event detection on EEG data. To enhance accessibility, a mobile application provides anesthesiologists with anytime, anywhere access to patient data and critical alerts. Remote dose adjustments are facilitated through the mobile app's synchronization with the fog computing platform. A cloud web application offers predictive insights into the patient's brain state.

Future research could focus on integrating additional sensors, such as those for heart rate variability and respiratory patterns, to provide a more comprehensive assessment of the patient's physiological state. Enhancing the cloud-based application to aggregate vital signs data from multiple sensors would enable anesthesiologists to gain a holistic view of patient conditions through a web-based dashboard. This cloud-based web application can serve as a centralized hub, providing anesthesiologists with an intuitive platform to monitor and interact with processed data. By integrating advanced Azure Machine Learning algorithms, the application can extract deeper insights from EEG and patient data, enhancing the accuracy of anesthesia depth estimation and early detection of potential complications. This empowers healthcare professionals to make informed decisions and respond swiftly to critical events [10].

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