



Remote Epilepsy and Seizures DAS for Alzheimer's Patients

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Abstract

Models may identify seizures using nearby biosensors like EEG and EMG. EEG and EMG frequency bands detect seizures. The proposed Data acquisition system (DAS) remotely records patients' cerebrum movements to treat mental diseases like epileptic convulsions. Functional-based seizure detection models have categorical restrictions, making them desirable. Biosensor technologies and IoT developments enable a real-time remote epilepsy health care system. The proposed system uses sensors and cloud storage to predict Alzheimer's illness.

Keywords: IOT, EEG, EMG, Epilepsy, Seizures

I. Introduction

Epilepsy, "a brain illness characterised by an ongoing tendency for epileptic seizures," has neurological, emotional, psychological, and social effects, according to Fisher. Epilepsy affects children and adults, with 4.8 to 8.2 per 1000 cases. Seizure recognition algorithms are used during pre-operative evaluations and retrospectively [1].

If the algorithm works, a seizure-alerting automatic alarm system may use it. This seizure tracking system could help doctors identify vocations with the highest seizure risk and their triggers. Electrical stimulation inhibits epileptic-like behaviours during seizures. A closed-loop system could identify electrographic seizures in real-time. Predictive seizure algorithms exist. Most classifiers, including fuzzy logic and others, employ extracted features as input. Vector machines with neural networks and feature/channel linear matrices Wavelet transformations, differential operators eigen-decomposition, and Gabor functions have extracted useful characteristics from recordings. Performances aren't perfect. Neuronal circuits may directly connect variables in physiologically dependent seizure detection models [10]. [3] Parameter alterations may evolve fundamental physiological systems. One model-based seizure detection approach exists. Scalp models created this pattern. It didn't foresee seizures. Electrodes on the scalp record the brain's electrical impulses and voltage changes in a short electroencephalogram (EEG). EEG data can reveal brain-related neurological and mental problems. Mental, neurological, or epileptic seizures can occur at any time. Seizures disrupt brain function,

affecting movement, perception, and behaviour [5].

Epilepsy diagnosis requires seizure prediction. EEG is also used to evaluate video content, compute alcohol intake, classify sleep stages, detect smoking-induced brainwave abnormalities, and use mobile phones [6]. Accurate categorization requires EEG feature extraction. EEG seizures were detected using wavelet- and Fourier-based feature extraction and classification [10].

Empirical mode decomposition may classify EEG data [7]. Empirical mode decomposition utilising a small dataset from Bonn University's open-source seizure database may predict future seizures. Wearable wireless sensors transmit EEG data to an IoT network. Validated seizure biosensors. Video and microphones monitor the patient's speech, movement, and expressions. Many patients transmit HD video and audio on the IOT channel. In Fig. 1, a neurologist or treatment centre evaluates and prescribes using Google Assistant-compressed data. Sight speed cannot transfer HD videos. If a wearable sensor fails Medicare guidelines, a hospital or police will be alerted. IoT's consistency and speed will hinder video encoding and real-time transmission.[2]

Proposed Methodology

A. Block Diagram:

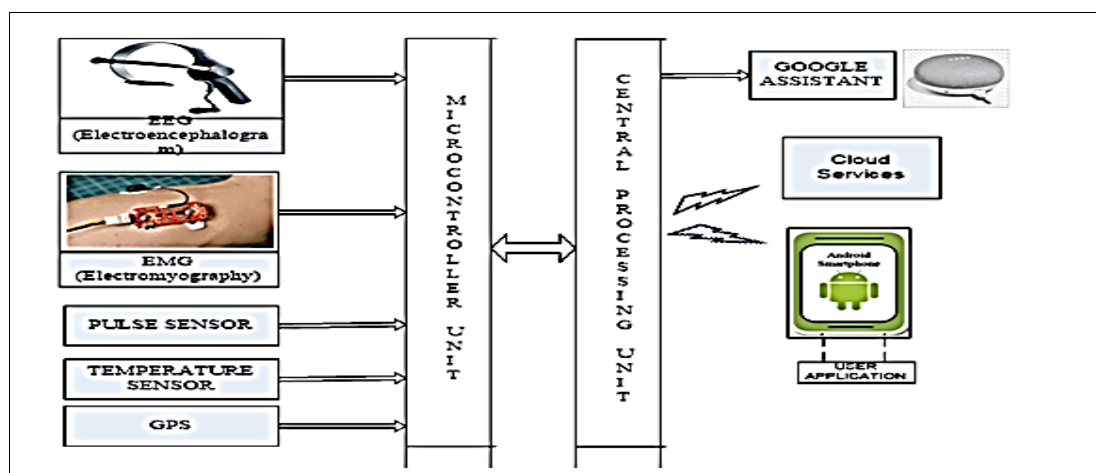


Fig. 1 Architecture diagram

Fig. 1 simulates an IoT framework. Brainwave and muscle activity sensors may be fitted to patients. The CPU, sensors, and microcontroller will communicate through serial connection. Prediction algorithms were created using machine learning and an Alzheimer's dataset. Doctors and carers receive health reports. Voice-activated devices assist patients take medications and exercise. EEG data analysis EEGs record microvolt-range scalp potential changes.

Analysing EEG data

Electroencephalograms detect scalp microvolt changes.

The circuit amplifies and filters twice. Microcontroller ADCs digitalized the signal. After applying saline to the amplifier, passive silver-plated electrodes are attached to the user's skull. The opto-isolated UART sends ADC values to the microcontroller via USB. The PC's C programme processes signals using the FFT and SVM. EEG signals were saved in a database to track our growth. Figure 2 shows the patient's electrode-equipped EEG hat.

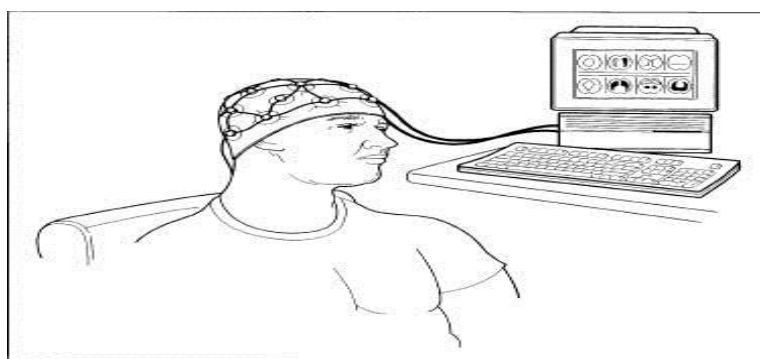


Fig 2 EEG electrode brain interface system

An EEG electrode, pulse, EMG and temperature sensors are connected to the patient and the patient's seizures are registered and investigated for the early detection of Alzheimer's disease in the elderly.

The logical framework

The project uses a differential instrumentation amplifier, an automotive amplifier, and filters to reduce DC offsets, 60 Hz power-line noise, and other distortions. ADCs digitise signals. USB UART transfers data to a PC. Brainwaves control the computer after the system processes the signal.

An internal block schematic of the EEG:

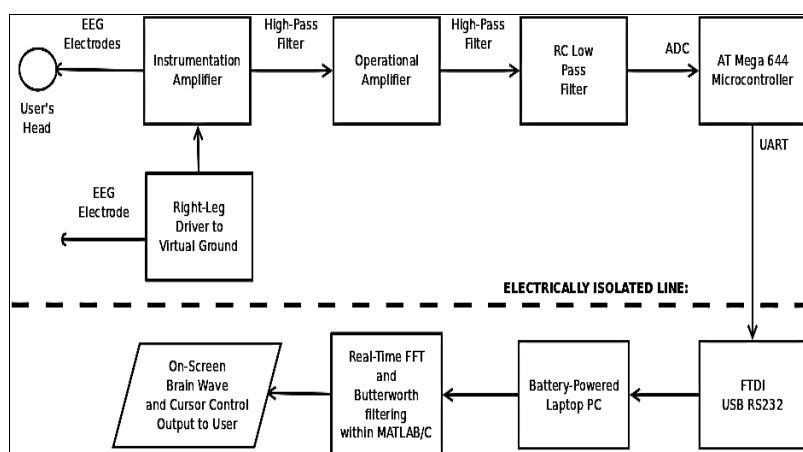


Fig 3 EEG Functional block diagram

With one resistor change, an instrumentation amplifier can change an amplifier circuit's gain. Differential amplifiers allow simultaneous resistor swapping, as we've discussed. Instrumentation

amplifiers generate power from differential amplifiers. Figure 4 Amplifier Instrumentation Circuit

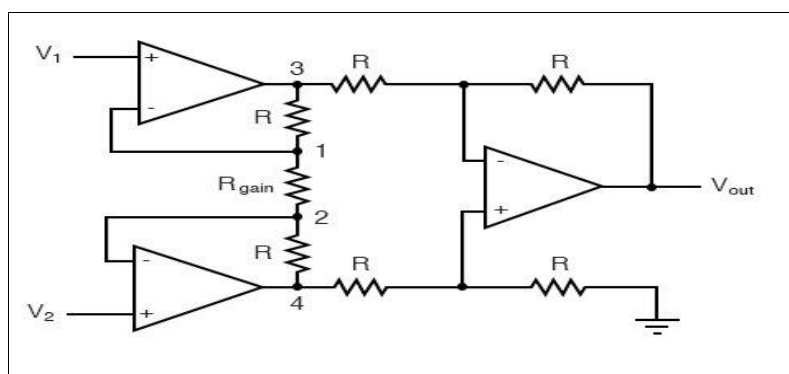


Fig.4 Internal Amplifier Circuit

Three additional resistors link the two buffer circuits in this powerful circuit. Except for R_{gain} , all resistors are assumed to have the same value except for R_{gain} . (1)

$$V_{3-4} = (V_2 - V_1) \left(1 + \frac{2R}{R_{\text{gain}}} \right) \quad (1)$$

Negative feedback from the upper-left op-amp equals V_1 at point 1 (the top of R_{gain}). V_2 maintains the voltage at point 2 (the lower end of R_{gain}) similarly. R_{gain} drops voltage by $V_1 - V_2$. Since the feedback loops of the two input op-amps draw no current, R_{gain} and the two "R" resistors above and below it must draw the same current.

$$A_V = \left(1 + \frac{2R}{R_{\text{gain}}} \right) \quad (2)$$

We discussed IoT data acquisition with sensors for EEG and EMG, transforming raw signal digital data for uploading to a cloud database, and healthcare network designs and networks that connect to the IoT backbone to transmit and receive medical data. Research has focused on healthcare. This article summarises IoT research on Alzheimer's illness, chronic disease management, private wellness programmes, and fitness management. This article discusses current sensors, computers, internet apps, and more to demonstrate the limitless scalability of IoT-enabled healthcare services and market dynamics and supporting technology. This article summarises eHealth and IoT laws for healthcare device evaluation. This research affects the Internet of Things and healthcare technology, thus researchers, engineers, healthcare practitioners, and politicians will be interested.

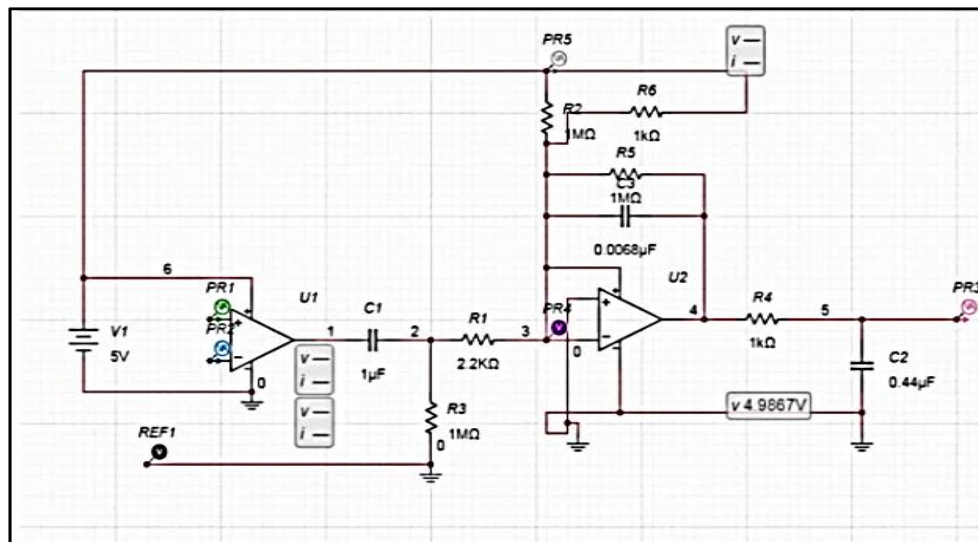


Fig.5 EEG Amplifier Functional circuit

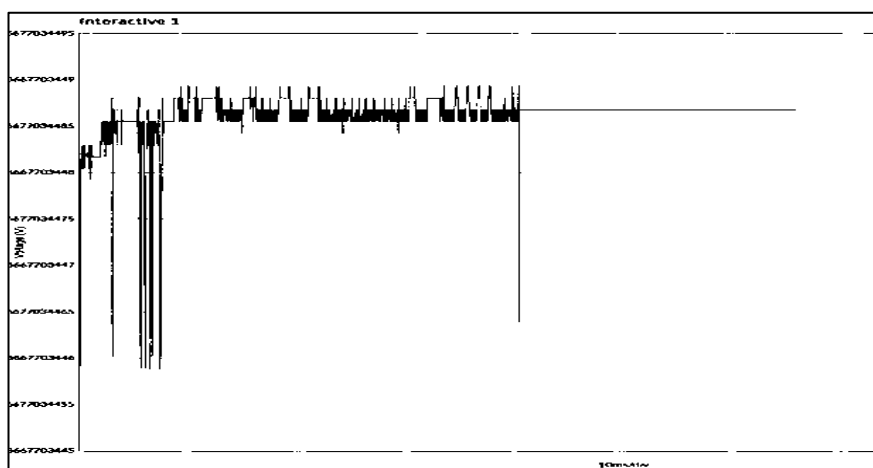


Fig 6. EEG Amplifier Schematic output results

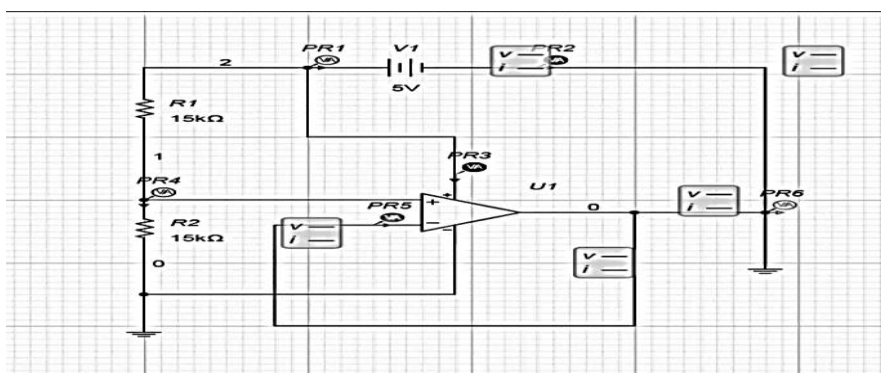


Fig.7 Microcontroller Circuit diagram

USB and microcontroller power were separated by a Fairchild Semiconductor 6N137 optoisolator. UART RX and TX pins D.0 and D.1 of the microcontroller are connected to the FTDI device through an isolation line. USB UART Opto-Isolation Schematic Fig.9

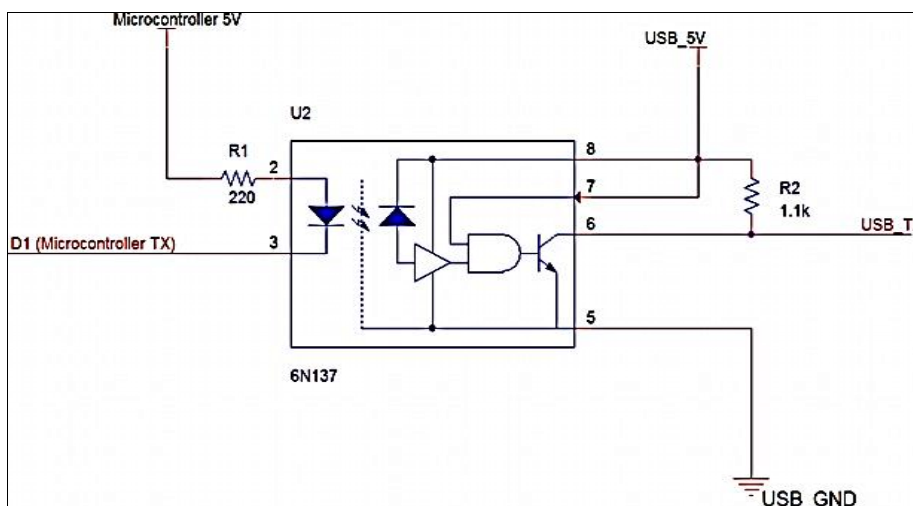


Fig.8 UART Opto-Isolation schematic circuit

Design of an Electrode Cap

The EEG electrode-attached sensor arm is placed on the forehead in front of the first eye (FP1). Eight hours on one AAA battery. We added EEG electrodes to a used baseball cap. Electromyography Data

II. EMG Sensor Measurement and Data processing

A. EMG signal collection

Neuromuscular illnesses have long been studied and diagnosed using electromyography (EMG). Prosthetics, robotics, and other control systems are using these sensors as microcontroller and integrated circuit technology advances. After choosing a muscle group, wash the skin. Put an electrode in the muscle. An electrode should also be parallel to the muscle. Stick the electrodes on your skin. Reference electrodes can be used on bony or non-muscular surfaces. Fig. 10 shows how to attach an ADC or microcontroller to a development board and arrange EMG sensors.

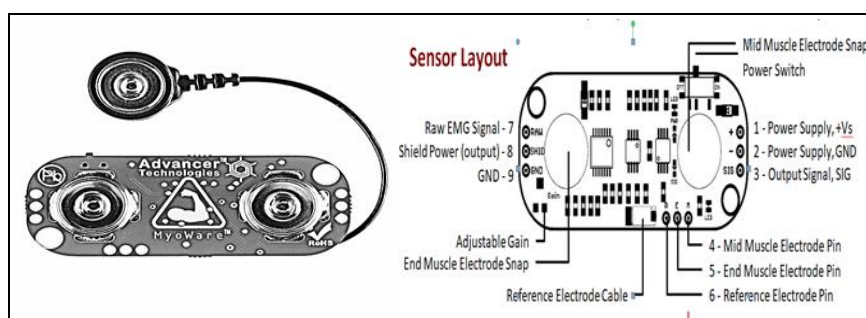


Fig.9 EMG data acquisition system

Muscle Sensors with microcontrollers require no assembly. Instead of employing an electromyography (EMG)

sensor that provides a raw EMG signal, we use a microcontroller's analog-to-digital converter (ADC) to process an amplified, rectified, and integrated signal (the EMG envelope). EMG signal fig.11 shows the difference.

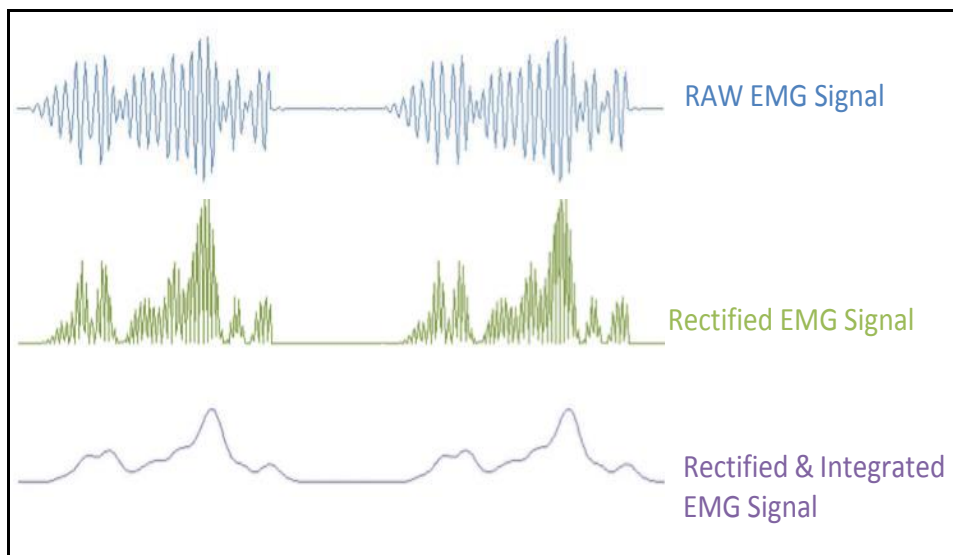


Fig.10 EMG output waveforms

The normal mode and differential mode voltages may be used to describe the cathode voltages, and vice versa, as shown in the schematic in Fig. 12. The midpoint between and is referred to as the "normal mode voltage."halfway between V_a and V_b .

$$V_{nm} = \frac{(V_b + V_a)}{2}$$

The voltage drop between the biceps terminals is the differential mode voltage.

$$V_{dm} = V_b - V_a$$

EMG electrode voltages (.) may be expressed in the following equations.

$$V_a = V_{nm} - \frac{V_{dm}}{2}$$

$$V_b = V_{nm} + \frac{V_{dm}}{2}$$

EMG Signal Power vs. Weight Calculation

Where P is the average "power" of the EMG circuit output signal, and N is the number of sample points. Each sample of the output voltage of the EMG circuit is represented by v_{ci} .

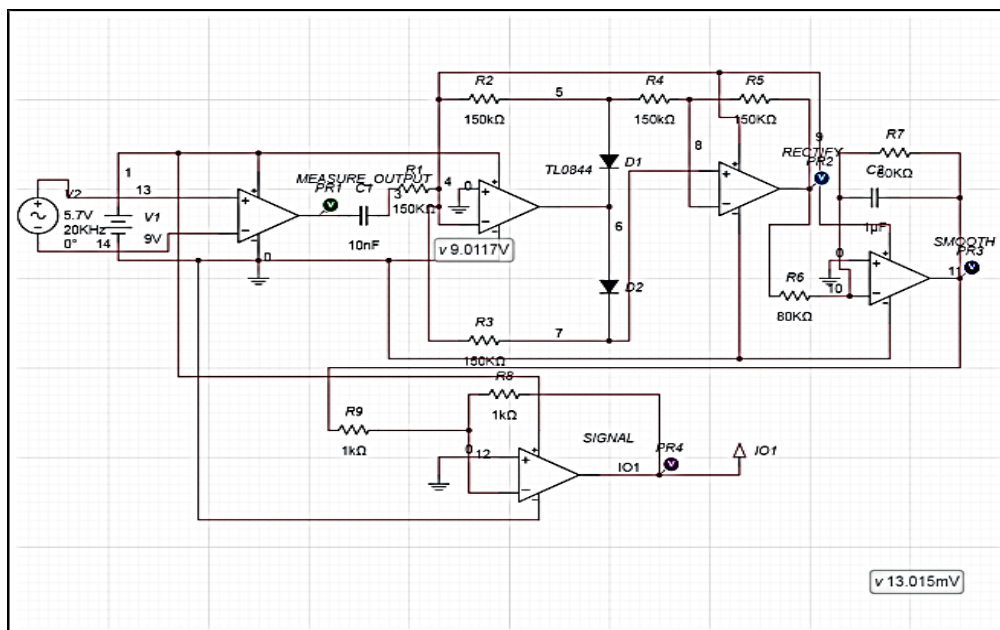
$$P = \frac{1}{N} \sum_{i=1}^N V_i^2$$


Fig.11 Schematic of EMG muscle circuit diagram

Measurements MultisimLive uses the NI Elvis III oscilloscope to compare simulated and measured EMG circuit waveforms. Differential enhancement generates EMG signals. With a gain of 10, the schematically constructed differential speaker needs a high input and low yield impedance. FIGURE 13:

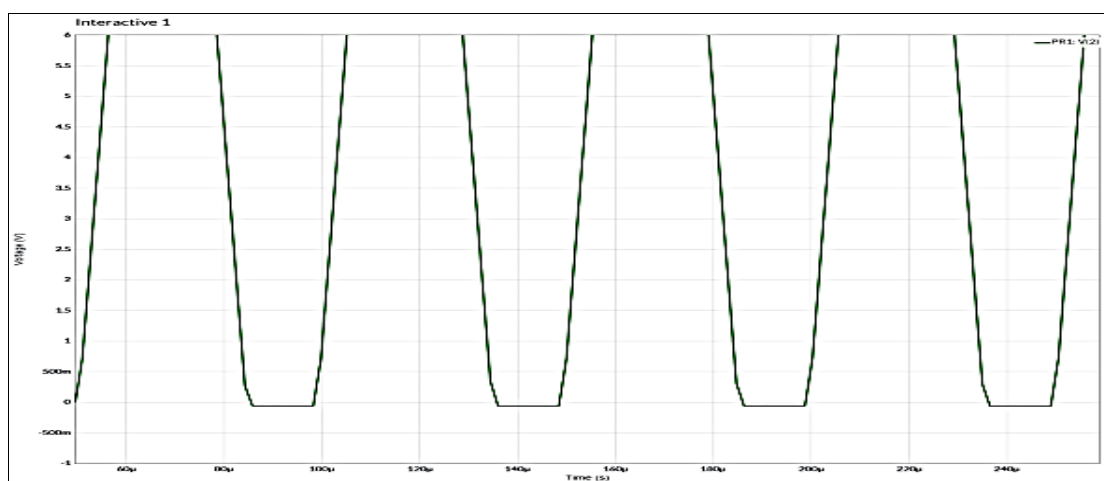


Fig.12 Raw Output EMG Signal

Degrading commotion frequencies might be as high or low as the primitive EMG signal. A high pass channel may be utilized to minimize low recurrence commotion generated by intensifier DC balances, sensor float on skin, and temperature fluctuations. Fig 14 depicts the waveform of an EMG signal after it has been corrected.

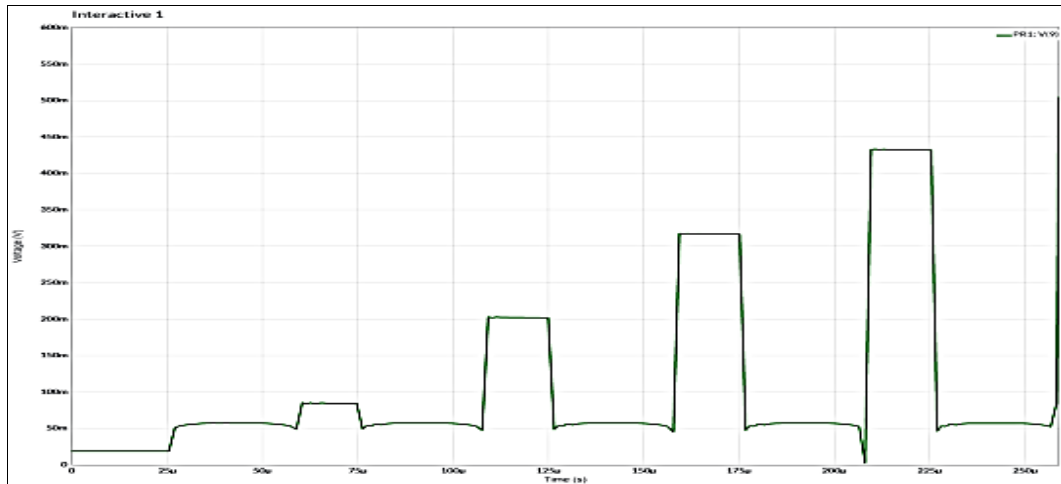


Fig.13 Rectified output EMG Signal

High and low recurrence commotion should be eliminated for the transmission of pure EMG. For this reason, only a certain frequency range should be passed on. A band pass channel may be used to make this possible. Fig. 15 depicts the EMG signal's smoother waveform.

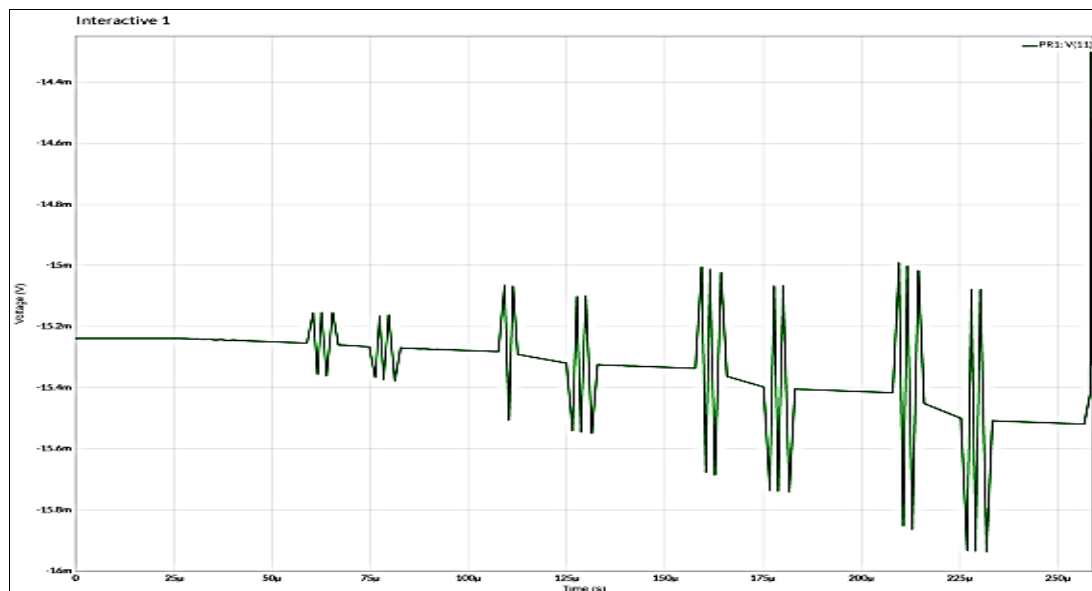


Fig.14 Filtered EMG Signal waveform

For muscles, however, the EMG response is ineffective. Figure 16 depicts the rectified and integrated EMG signal.

Voltage readings are sent to the serial monitor via reading an analogue input on pin 0. The serial plotter (Tools > Serial Plotter menu) provides a visual representation of the data. A potentiometer's centre pin should be connected to pin A0.+5V and ground on the external pins. Take the analogue data and convert it to voltage (which ranges between zero and 1023). (0 - 5V)

III. IOT Networking:

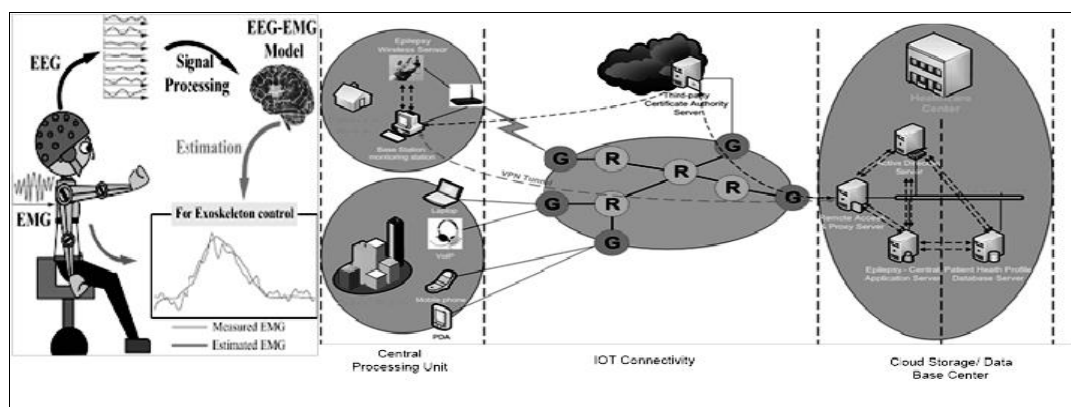


Fig. 15 Four layered IOT Architecture for remote data acquisition system

In this paper, we explore the current state of centralised real-time remote health treatment for epilepsy patients and the opportunities and difficulties that lie ahead for the field. Using a wireless communication network, wearable sensors may record and transmit EEG data in real time. There have been recent proposals, developments, and evaluations of biosensor sensors for monitoring epileptic seizures. An accelerometer, gyroscope, and magnetometer, all of which monitor motion, would be required to monitor the patient's hands. The patient's voice, movements, and expressions are also recorded by cameras and microphones.

By Multiple patients can now receive live, high-quality video and audio with a single IoT connection. The information is then compressed and sent to a neurologist or medical institution. Reduced transmission quality due to slower sight speed. When a sensor worn on the body registers a value below a Medicare-defined threshold, the IoT network can send a notification to the relevant healthcare facility. The consistency and quickness of IoT will create obstacles for image compression and real-time rendering. These enhanced connections may persist if the Internet of Things gains traction. Family members and carers can use the site to learn more about a patient's condition. Data from wireless sensors are collected at central hubs and stored, encrypted, and protected. Correct medical data is now readily available to specialists. It will be a crucial piece of evidence in future studies aimed at bettering healthcare. Movement sensing, sensor power supply, and epilepsy detection techniques are all examples of standards for wireless sensor devices. Everything else about the

machine's design is the same.

IV. Conclusion:

We have covered IoT data acquisition with sensors for electroencephalography (EEG) and electromyography (EMG), as well as the conversion of raw signal digital data for uploading to a cloud database, as well as healthcare network architectures and networks that enable connectivity to the IoT backbone to transmit and receive medical data. The healthcare industry has been a primary target of IoT research. Many research are summarised in this page, including ones on the effects of IoT on private wellness, fitness management, monitoring therapy for Alzheimer's patients, and the management of chronic diseases. In order to show that IoT-enabled healthcare services and market dynamics and supporting technology can grow indefinitely, this article discusses recent developments in sensors, computers, internet applications, and more. To aid with the assessment of healthcare technologies, this page provides a summary of relevant eHealth and IoT regulations. Researchers, engineers, healthcare professionals, and policymakers will all be interested in this work because of the implications it has for the Internet of Things and healthcare technologies.

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