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Generalized Epileptic Seizure Alert System

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***Abstract*—Generalized Epileptic Seizure Alert System is a medical device that detects epileptic seizures and then with the use of a buzzer, sound is emitted as an auditory alert system. The buzzer sound alerts the caretaker of the patient or a nearby person to assist the patient during the attack and take care that the patient does not get hurt by the surroundings or fall down as the patient loses control. The device consists of an accelerometer which is used to sense the vibrations caused during the epileptic attack and is computed by a micro-controller which takes the data from the accelerometer and checks whether the vibration sensed is within limits or not which is programmed in it, if the detected vibration is more than the programmed data then the micro-controller sends the signal to the buzzer and the buzzer emits noise. In the literature, it is presented that the limit of the vibration produced will be +/- 2g acceleration unit. We created a virtual circuit of the device using the software Tinkercad where a virtual Arduino was used as a microcontroller and a virtual LED as an output as it was for better visual representation than an auditory one. The results achieved through the testing were successful. Our model was tested using an open-source dataset and produced 73.53 percent accuracy in predicting epileptic seizures.**

***Index Terms*—Accelerometer, Arduino, Epileptic Seizures, Sensing**

I. INTRODUCTION

Epilepsy is a central nervous system (neurological) disorder in which brain activity becomes abnormal, causing seizures or periods of unusual behavior, sensations, and sometimes loss of awareness. Approximately 12 million out of the 70 million persons with epilepsy (PWE) worldwide are expected to be Indians, which is close to one-sixth of the global population [1]. Seizures are of many kinds with the most prevalent being generalized tonic-clonic seizures. This disturbance is caused by electrical signals spreading inappropriately through the brain. Sometimes this causes the muscles, nerves, or glands to receive these signals. In the brain, these signals can lead to loss of consciousness and cause severe muscle contractions [2]. Various technical papers and studies were referred to and the frequency which was generally set was of 5 to 10 Hz and acceleration points up to 250 units for +2 to -2 g. Although there are cases of false positives, the cases of false positives are lower [3][4].

The aim of this project is to develop a battery-powered, low-cost, portable generalized tonic-clonic seizure alert device that can notify nearby family members or caregivers when a seizure occurs through alarm alerts. A caregiver can then help the person during and after the seizure. For example, they can help reposition the person, making sure they are on their side if they are not conscious. The project aims to use an Inertial Measurement Unit/tri-axial accelerometer as the primary sensing unit coupled with advanced signal processing to detect abnormal motions akin to seizures in the patient's body.

II. LITERATURE REVIEW

Epilepsy is one of the most prevalent diseases in the world. Uncontrolled seizures, caused due to epilepsy, contribute greatly to the economic, social, and personal burden. Nearly 1% of the entire population suffers from epilepsy [2].

15% of the entire cost due to epilepsy is spent on diagnosis and medical resources which are the direct costs and the remaining 85% are the indirect costs which include lost earnings and reduced household activities attributed to epilepsy-related morbidity and mortality. Due to this, any attempt to extenuate the effects of epilepsy is well-motivated [2].

Seizure detection generally describes the instantaneous detection of an epileptic seizure that alerts for the right assistance in situations that require immediate intervention. In addition, seizure detection contributes to benefits that are long-term in nature, due to the data collected on the different seizure types, frequencies, and their deviations causing more suitable day-to-day care and improved handling of antiepileptic drugs. This study mainly focuses on the detection of a seizure [5].

Electroencephalography (EEG) measurement systems cannot be considered practical for everyday life. Patients are reluctant to wear EEG electrodes for the detection of epilepsy for a longer period of time. It is a tedious task and these approaches are resource- and labor-intensive. The single triaxial accelerometer can also be fixed on the wrist of the patient to detect epileptic seizures [2].

Accelerometers can detect changes in direction and velocity. Changes in the x, y, and z axis can be detected by the "3-D accelerometers". Motion sensors are a relatively recent tool for seizure detection. These devices may be used to detect movement seizures including tonic–clonic and myoclonic seizures. Accelerometers can only be used to track recurring seizures. Accuracy can be affected due to movements similar to seizures such as stumbling and sudden gestures [6].

The first actigraph sensors were used in a preliminary study with 18 patients, which was published in 2005 and relied heavily on expert analysis of the recording system [7]. In this study, motion sensors on the chest, wrists, and ankles detected only 48% of the seizures resulting in poor accuracy.

The Epi-Care Free system which is a 3D accelerometer was also tested. It has a transmitter which transmits real-time accelerometric data to a control system. It detected almost 90% of seizures in the study of 20 people who had 39 generalized tonic–clonic seizures during the experiment [5].

Several technical papers and journals discussed above only talk about monitoring and sensing epileptic attacks but our project takes a further step regarding the alert system in addition to sensing and monitoring.

Most of the sensing devices have good accuracy in detecting epileptic seizures, but they also produce a high false positive rate. This is due to the sudden movement of arms caused by walking, stumbling, and running. This could be very irksome for the patients as the false positives could interrupt their daily life activities. Our model focuses on both increasing the seizure prediction accuracy as well as decreasing the false positive rate.

III. MATERIALS AND METHODS

A. Materials

1. Arduino Nano: It is a microcontroller device that will be used to read data from the accelerometer and control the buzzer. It is compact in size so as to reduce the total size of the device and also easy to program. It has all the functionality of an Arduino Uno.
2. Tri-axial Accelerometer: It consists of 3 accelerometers ranging from –5 to +5 g which is mounted in one small block. Coupled with proper data collection hardware and software we can get graphs and calculate the magnitude of the net acceleration.
3. Buzzer: A buzzer or beeper is an audio signaling device, which may be mechanical, electromechanical, or piezoelectric.
4. Printed Circuit Board: It is used to assemble all the various all the various components into one board
5. DC Battery: It is used as a power source for the components

For testing and analysis, an open-source software Tinkercad was used.

B. Method

The Arduino Uno and accelerometer are connected through the SDA and SCL pins. The accelerometer is powered by connecting the VCC and GND pins of both Uno and the accelerometer.

The Arduino then checks if the data received through the accelerometer are within range or not and if not it sends it data through its PWM pins which is the 9th PWM pin

Then from the output pin of the Arduino if the readings are outside the programmed range it will send a signal to the buzzer The buzzer connected through the breadboard with a resistor will start emitting until the vibrations are within range

C. Experimentation setup

A virtual circuit of the device was created using the software Tinkercad where a virtual Arduino Uno was used as a micro-controller and a virtual LED as an output as it was for better visual representation than an auditory one. All the connections were made using a mini breadboard and the tri-axial accelerometer used was Sparkfun MMA7361 Breakout which had a g-select input that switches the accelerometer between ±1.5g and ±6g measurement ranges. The ±6g acceleration detection range was used for the testing. A push button was connected to turn off the LED and buzzer. Figure 1 shows the full circuit designed in Tinkercad.

The Analog pins A0, A1, and A2 of Arduino were connected to the XOUT, YOUT, and ZOUT pins of the accelerometer respectively. The g-select pin was connected to the digital pin D8 which was set to high voltage. This sets the acceleration range detected by the accelerometer to ±6g. The buzzer and LED were connected to the D13 pin and the push button pin was connected to the D12 pin. The components are powered by the 3.3V pin of Arduino.

To avoid the case of false alarms and smoothen the output readings, our model takes 20 accelerometer readings together and averages them. The readings are taken every 200 ms, so the frequency is 5 Hz. Thus, the algorithm checks for a positive case of epilepsy every 4 seconds. This model uses 2g as the trigger range for seizure detection.

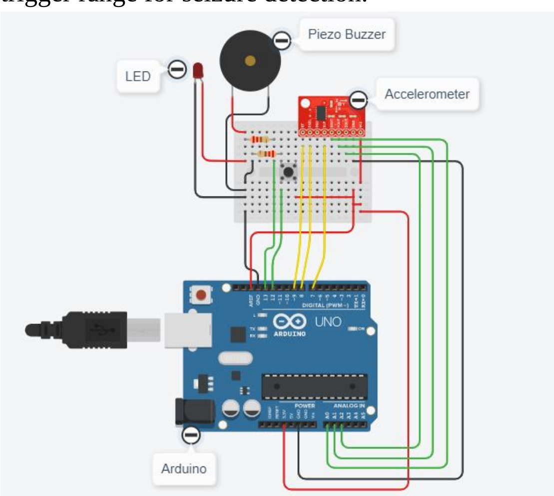

Fig. 1. Full circuit design

The formula used for converting the raw accelerometer reading (A_{raw}) into acceleration units of g-force (A_g) in a 10-bit ADC microcontroller is as follows:

$$A_g = \frac{(A_{raw} - 511.5)}{1023} \times \frac{Vs}{sensitivity} \qquad (1)$$

where *Vs* is the supply voltage and *sensitivity* is the accelerometer's sensitivity in V/g. Both supply voltage and sensitivity values were referred from the accelerometer's datasheet.

The total g-force is calculated by finding the square root of the sum of squares of the x, y, and z-axis acceleration values. The value of the total g-force will always be positive. So the algorithm checks if the value is below or above +2g. If the total acceleration is below 2g, the condition will be considered normal and if it falls above 2g, it will be detected as a positive case of epileptic seizure.

IV. RESULTS AND DISCUSSION

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he circuit and code were tested with two cases, each having different inputs. In Case 1, the circuit was simulated and then the accelerometer was activated. Figure 2 shows the Serial Monitor readings obtained from Case 1 and Fig. 3 and Fig. 4 show the results that were obtained from the circuit when the total acceleration g-force is in the normal range (<2g) and in the critical range (>2g) respectively.

From the Serial Monitor readings, it can be inferred that there is always an acceleration of +1g acting on the device. This is due to the gravitational force along the z-axis.

When the accelerometer is activated, it only moves the component with an acceleration of +1g and -1g in the x-axis. Since there was this restriction on the movement of the accelerometer in the simulation, the x-axis readings were scaled to verify the response of components for other outputs.

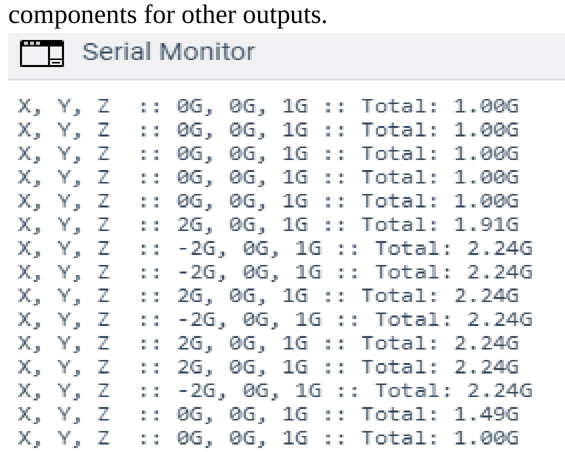


Fig. 2. Serial Monitor output for Case 1

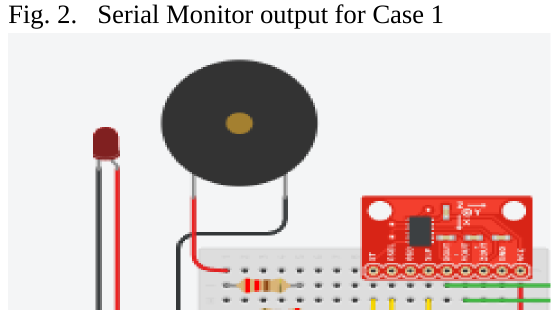


Fig. 3. LED and buzzer off in normal range

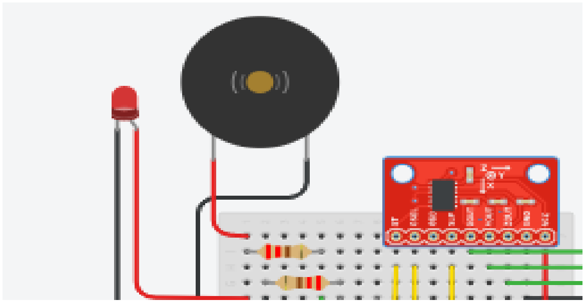


Fig. 4. LED and buzzer turn on in critical range

The LED and the buzzer turned on when the accelerometer readings were above the 2g range as shown in Fig. 4. And pressing the push button resets both the components. This verifies the correctness of the circuit design.

The main limitation in the testing in Case 1 was the restriction on the freedom of movement of the accelerometer in the virtual environment. To overcome this, further experimentation was carried out in Case 2.

In Case 2, experimentation was carried out using an open-source dataset [8]. The dataset consists of 6 participants performing 4 different activities: walking, running, sawing, and seizure-mimicking seated, using a tri-axial accelerometer on the dominant wrist. The mimicked seizures were trained and controlled, following a protocol defined by a medical expert.

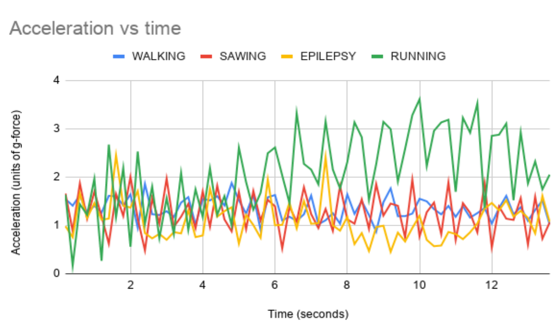
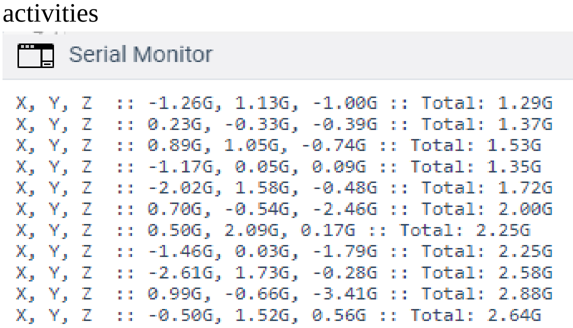


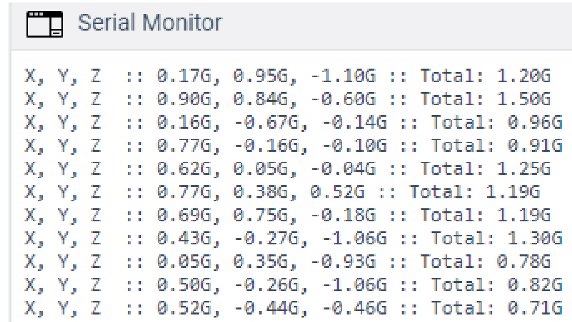
Fig. 5. Graph of total g-force against time for various activities



Serial Monitor

```
X, Y, Z  :: -1.26G, 1.13G, -1.00G :: Total: 1.29G
X, Y, Z  :: 0.23G, -0.33G, -0.39G :: Total: 1.37G
X, Y, Z  :: 0.89G, 1.05G, -0.74G :: Total: 1.53G
X, Y, Z  :: -1.17G, 0.05G, 0.09G :: Total: 1.35G
X, Y, Z  :: -2.02G, 1.58G, -0.48G :: Total: 1.72G
X, Y, Z  :: 0.70G, -0.54G, -2.46G :: Total: 2.00G
X, Y, Z  :: 0.50G, 2.09G, 0.17G :: Total: 2.25G
X, Y, Z  :: -1.46G, 0.03G, -1.79G :: Total: 2.25G
X, Y, Z  :: -2.61G, 1.73G, -0.28G :: Total: 2.58G
X, Y, Z  :: 0.99G, -0.66G, -3.41G :: Total: 2.88G
X, Y, Z  :: -0.50G, 1.52G, 0.56G :: Total: 2.64G
```

Fig. 6. Serial Monitor output for running data



Serial Monitor

```
X, Y, Z  :: 0.17G, 0.95G, -1.10G :: Total: 1.20G
X, Y, Z  :: 0.90G, 0.84G, -0.60G :: Total: 1.50G
X, Y, Z  :: 0.16G, -0.67G, -0.14G :: Total: 0.96G
X, Y, Z  :: 0.77G, -0.16G, -0.10G :: Total: 0.91G
X, Y, Z  :: 0.62G, 0.05G, -0.04G :: Total: 1.25G
X, Y, Z  :: 0.77G, 0.38G, 0.52G :: Total: 1.19G
X, Y, Z  :: 0.69G, 0.75G, -0.18G :: Total: 1.19G
X, Y, Z  :: 0.43G, -0.27G, -1.06G :: Total: 1.30G
X, Y, Z  :: 0.05G, 0.35G, -0.93G :: Total: 0.78G
X, Y, Z  :: 0.50G, -0.26G, -1.06G :: Total: 0.82G
X, Y, Z  :: 0.52G, -0.44G, -0.46G :: Total: 0.71G
```

Fig. 7. Serial Monitor output for seizure data

The sampling frequency of the dataset was 16 Hz. Therefore, the data had to be preprocessed to be of 5 Hz, which is how frequently our device collects readings. The algorithm was tested on about 30 datasets of each activity

Figure 5 shows the graph of total acceleration g-force plotted against time for a dataset for each activity. From the graph, it can be observed that the total g-force always stays below 2g for walking and sawing. In seizure, the acceleration sometimes increases above the 2g range. But in the running data, the total g-force is mostly above the 2g range.

The data were fed into the algorithm, which takes 20 readings together and averages them. From the walking and sawing output, it was observed that the average total acceleration always stays below 2g. It produced a 100% accuracy on both activities.

But in the running data, the averaged g-force mostly falls above the 2g range. The model produced 23 false positives out of 36 total cases having an accuracy of 36.11%. Moreover, the algorithm failed to detect the majority of the epilepsy readings as a positive case. It had a very poor accuracy of 5.88% (2/34).

Figure 6 shows the Serial Monitor output of the running data where it can be seen that many acceleration values fall above the 2g range raising the false alarm. However, in Fig 7, the majority of the readings are below the 2g range for the seizure data.

Due to the poor result in both running and epilepsy data, the dataset was tested on various other parameters. Two frequencies, 5 Hz and 16 Hz, were used to check the performance of the model on different trigger ranges and sampling sizes. Various trigger ranges used were 2g, 1.9g, 1.8g, 1.75g, 1.7g, 1.6g and 1.5g. The sampling size was varied from 1 to 30. Sampling size is the amount of readings taken together to average.

Table 1 shows some of the combinations of parameters giving good accuracy. From the experimentation, it was observed that the data gave good accuracy on two models.

The first one uses a frequency of 5 Hz, a trigger range is 2g and does not take an average. It instead takes the readings one by one and makes the decision. This model gave an accuracy of 81.08% (30/37) on the walking data, 50% (15/30) on the sawing data, and 73.53% (25/34) accuracy on the epilepsy dataset.

The second model also takes readings at a frequency of 5 Hz. But it uses 1.7g as the trigger range and a sample size of 2. This model produces 83.78% (31/37) accuracy on the walking data, 70% (21/30) on the sawing data, and 67.64% (23/34) accuracy on the epilepsy dataset.

The main limitation of both models is that it has 0% (0/36) accuracy on the running dataset. This is due to the rapid motion of the arms caused when the person is running fast or sprinting.

Table I. Accuracy of the model on varying parameters

Frequency	Trigger	Sampling Size	Walking	Sawing	Running	Epilepsy
	2g	20	100	100	36.11	5.88
	2g	1	81.08	50	0	73.53
	1.9g	1	67.56	36.67	0	82.35
5 Hz	1.7g	2	83.78	70	0	67.64
	1.6g	3	89.18	66.67	0	61.76
	1.6g	2	64.86	46.67	0	76.47
	1.5g	3	78.37	43.33	0	67.64
	2g	20	100	100	33.33	5.88
	2g	1	67.56	43.33	0	85.29
16 Hz	1.8g	2	62.16	40	0	73.52
	1.7g	3	64.86	53.33	0	58.82
	1.5g	5	48.64	53.33	0	73.52

The circuit and the components responded accurately to the readings in Case 2. Whenever the output falls above the trigger range, the device detects it as a positive case of epilepsy and triggers the alarm. Despite some false positives (due to running, sprinting, or jumping), the improved model holds a good accuracy in the detection of the mimicked seizures.

This verifies the correctness of the Arduino code and the preprocessing carried out on the accelerometer readings. Thus, from the positive results in the two cases, it was concluded that the experiment was successful.

This device can be placed on an epilepsy patient's limbs. In a generalized tonic-clonic epileptic seizure, the patient's limbs will shake mildly or violently. If the total acceleration of the limbs is above the 2g range, the device will detect it as a positive case of epileptic seizure. This will trigger the buzzer which can alarm the nearby family members or caregivers.

In case of a false alarm, the patient can turn off the buzzer with the button.

Our future works include the fabrication of the device. The circuit connections and Arduino code developed in the virtual experimentation have to be applied to the physical components. This device can be further programmed to alert the patient's family members or caretaker via a smartphone application. This can not only be a more reliable alert system but also help in recording the seizures. These logs can be very helpful in the patient's epilepsy therapy trials. The model should be tested on other datasets to make sure it is not overfitting on one dataset.

While the algorithm was accurate in predicting the walking and sawing activity data, it recorded a very high rate of false positives for the running data. This is due to the quick motion of arms while sprinting or running fast. A machine learning algorithm can be developed and trained to learn the differences in the pattern of the false positive data and the seizure data. This will improve the accuracy of the device.

VII. CONCLUSION

The results achieved through virtual testing in Tinkercad software were positive. Thus, the circuit connections and the Arduino codes are correct. A similar procedure has to be implemented on the physical components. The device can be further programmed to give a notification alert on the caretaker's smartphone via an application.

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