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Detection of Tremor Syndrome Among Individuals with Tremor using Eating Aided Spoon for Recovery Monitoring

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Abstract

This study presents a system for detecting and monitoring tremor syndromes, aiming to improve the quality of life of people suffering from tremors. The core of this system combines a specially developed tablespoon and smartphone integration to create a comprehensive tool to assess the severity of tremors and provide personalized recommendations. The technical backbone of this solution lies in the integration of an ESP32 microcontroller and an advanced 3-axis gyro sensor that closely measures the angular velocity of hand movements. This data is extremely important for providing a nuanced understanding of the strength of shaking experienced by users. The user experience is further enhanced with the integration of the Blynk mobile application, allowing individuals to seamlessly track average tremor vibrations. This application acts as a channel to send data from the ESP32 microcontroller to the smartphone and allows the user to visualize the tremor intensity using an angular velocity graph. A notable feature of this system is the ability to convert accelerometer values to frequencies, which facilitates the creation of additional angular rate graphs that effectively represent hand tremors. The Blynk app can be a powerful tool for users as it not only allows them to monitor their own tremors, but also gives them insight into the specific type of tremors they may be experiencing. The system takes an important step beyond the data visualization aspect by providing personalized advice based on the type of tremor identified. This proactive approach allows users to take preventive measures and potentially reduce the progression of the disease. The innovative synergy between the table spoon, microcontroller, gyro sensor and smartphone application turn this system into a comprehensive solution that goes beyond simple monitoring. This becomes a dynamic tool for diagnosis, self-management, and intervention.

1. Introduction

Involuntary, rhythmic, oscillatory movements are the hallmark of tremor, a common movement disorder that can affect one or more body parts. Clinical features, tremor characteristics, history, and etiology are taken into consideration when classifying tremor. It may be the main symptom or the first sign of several different diseases. Essential tremor is a common tremor syndrome that is typified by a prominent postural tremor in the hands and forearms, possibly accompanied by a kinetic component. It can worsen over time and make it harder to perform daily tasks like eating, speaking, or writing, even though it is not fatal. There are various tremor syndromes, including task-specific tremor, physiologic tremor, Parkinson's disease tremor, and cerebellar tremor. Medication, counseling, or surgery may be used to treat tremor, depending on the underlying cause and degree of symptoms. Based on a comprehensive evaluation of the patient's medical history and physical examination, tremor is diagnosed [1].

Various tremor syndromes exhibit distinct characteristics, causes, and treatment approaches. Intention tremor, associated with cerebellar dysfunction, impacts limb coordination and speech during intentional movements, necessitating careful differentiation from physiological tremors. Holmes tremor, linked to brainstem lesions or strokes, manifests as a combination of postural, rest, and action tremors with slow but pronounced movements. Rest tremor, a hallmark of Parkinson's disease, involves a "pill-rolling" motion and is suppressed during voluntary movements. Enhanced physiological tremor, a benign condition, manifests as a high-frequency, low-amplitude tremor often triggered by stress or fatigue. Essential tremor, affecting up to 5% of the population, involves rhythmic movements and may have a genetic component. Primary Orthostatic Tremor (POT) presents rapid leg tremors while standing, and its distinct clinical nature is debated. Psychogenic tremor, rooted in psychological factors, involves rhythmic movements associated with specific triggers and requires a multidisciplinary approach for effective management. Each tremor type requires careful diagnosis and tailored treatment strategies.

The concept of using an eating aid spoon integrated with a gyro sensor and microcontroller to detect and classify tremor syndromes is innovative. This solution not only assists individuals with tremors in their daily activities but also provides valuable data for diagnosing and understanding the specific type of tremor. By converting hand movements into an angular velocity graph and then into frequency units, this approach could offer a comprehensive profile of tremor patterns. The integration with a smartphone app further enhances its usability for both patients and caregivers, providing real-time data and insights for informed decision-making and personalized treatment plans. This initiative shows promise in improving the quality of life for those affected by tremor syndromes.

The research encompasses various innovative approaches to detecting and monitoring hand tremors. Bhattacharjee & Bandyopadhyay (2019) aimed to develop a flexible paper touchpad for real-time monitoring of Parkinson's hand tremors. The advantages of their approach lie in the touchpad's flexibility, offering unobtrusive monitoring, portability, and cost-efficiency. However, further validation in clinical settings is necessary for accuracy, especially in detecting milder tremors [2]. Shi & Chiao (2016) focused on an inductive sensor-based contactless hand tremor detector, minimizing physical discomfort associated with sensors. While providing continuous and real-time tracking, their approach may be susceptible to electromagnetic interference and requires calibration for precise tremor detection [3].

Kalaivani Chelappan et al. (2019) developed a mobile app for tremor detection, leveraging integrated sensors in smartphones. The advantages include convenient remote monitoring, widespread accessibility, and an intuitive user interface. However, reliance on the built-in sensors may necessitate additional validation across diverse patient populations [4]. Ibáñez et al. (2013) proposed an online movement intention detector based on EEG signals. This non-invasive approach enables continuous monitoring and adaptive identification of tremor-related signals, potentially aiding in rehabilitation. However, the susceptibility of EEG signals to noise and artifacts requires precise electrode placement and preprocessing, demanding further validation for reliable performance across various patient populations [5].

De Marchis et al. (2012) suggested an improved technique for surface EMG signals-based tremor identification. Their method provides temporal tracking using widely available surface EMG electrodes. Although offering a non-invasive approach, it requires precise signal preprocessing and electrode placement and is limited to detecting tremors using surface EMG signals, particularly those with significant amplitudes or lower frequencies [6]. In summary, each research effort introduces unique advantages and potential applications for monitoring hand tremors in Parkinson's disease. However, challenges such as the need for validation, susceptibility to interference, and limitations in signal detection should be addressed for these technologies to achieve widespread and reliable clinical use.

2. Material and Methods

The development process for the suggested detection of tremor syndrome among individuals with tremor using eating aided spoon for recovery monitoring will be covered in this part. The prototype's general block diagram and the process flow chart are shown in the first subsection.

2.1 Block Diagram

Fig. 1 shows the setup of prototype, the gyro 3-axes sensor plays a crucial role in measuring the angular velocity along three axes (X, Y, and Z) to determine the orientation or rotation of a device. The sensor provides real-time data reflecting the device's movement to the ESP32 controller. The ESP32 controller serves as the central processing unit that communicates with external sensors and connects to the internet. It acts as the intermediary between the gyro sensor and the cloud platform. The ESP32 reads the sensor data provided by the gyro and performs necessary processing or filtering operations to refine the raw sensor readings. The processed data is then transmitted from the ESP32 to a cloud platform. In this work, the chosen cloud platform is Blink, a cloud-based service that specializes in receiving, storing, and processing data sent by IoT devices. Blink acts as a hub where the data from the gyro sensor can be securely uploaded and stored for further analysis and utilization. Once the data reaches the cloud platform, it can be accessed, managed, and analyzed remotely. This opens up a range of possibilities for monitoring, visualizing, and integrating the gyro sensor data with other cloud-based services or applications.

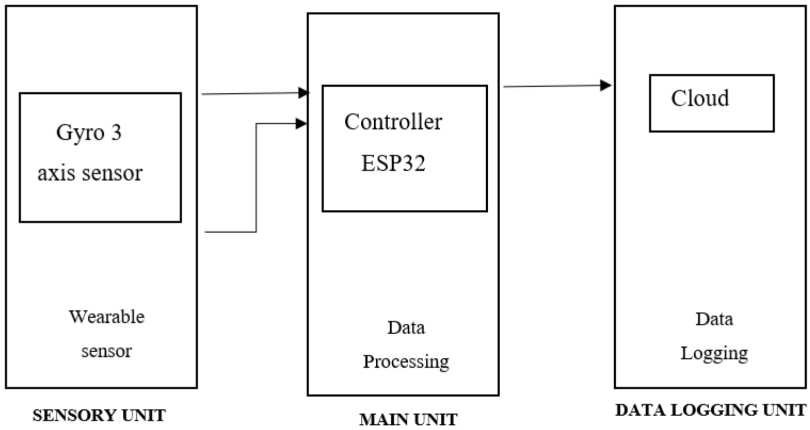

Fig. 1 *Block diagram of the study*

2.2 Process Flow Chart

Fig. 2 shows the steps involved in transmitting information from an MPU6050 gyro sensor to the Blynk platform and tracking vibrations.

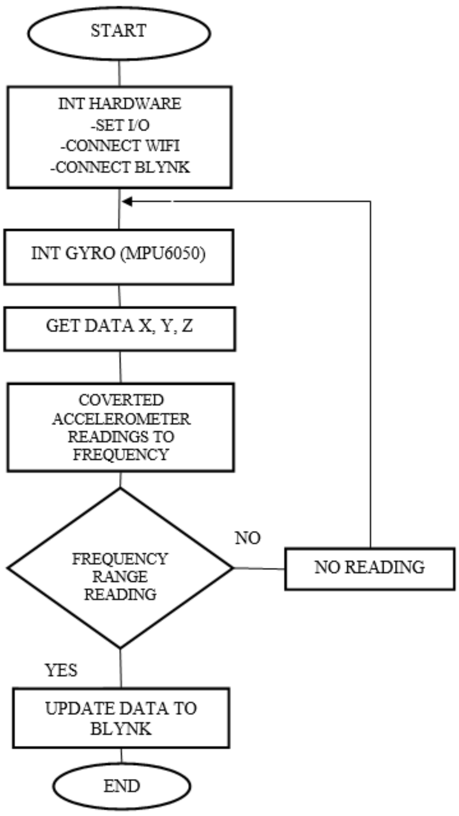

Fig. 2 *Flowchart of research methodology*

The process starts by configuring the input/output (I/O) connections, initializing the required hardware, and creating a WiFi connection. After that, it connects to the Blynk platform, enabling remote device monitoring and control. The gyro sensor (MPU6050) is then configured to record orientation and motion data. As the flowchart progresses, the sensor's data are specifically retrieved for the X, Y, and Z-axes values. The flowchart calculates the average vibration and convert it from accelerometer readings to frequency value. It establishes whether the reading of frequency is available, a notification (NOTi) is delivered, indicating a considerable vibration. If there is a no frequency reading, no notification is provided. The flowchart then uploads the data to the Blynk platform, enabling real-time viewing, tracking, and vibration data analysis.

3. Result and Discussion

3.1 Operation of the Prototype

Fig. 3 shows complete prototype of the tremor detector device. Power supply used was 3.7v battery that can operate for ESP32 and gyro sensor was at the side of the box, Device also have an ON/OFF switch. When the switch ON, the sensor will be detected accordant to the vibration. The test needs to be done in resting position due to capture the accurate vibration of the hand.

Fig. 3 *Prototype*

3.2 Blynk Interface

Fig. 4 shows the data stream of both Frequency and Average vibration. Frequency data refers to the information captured by the gyro sensor based on the movement direction. Initially, the gyro sensor provides accelerometer readings which are then converted to frequency to determine the range of actual tremor syndrome. Average vibration is calculated by dividing the sum of the x, y, and z values by 100. There are also automated notifications that indicate the type of tremor syndrome based on the frequency range.

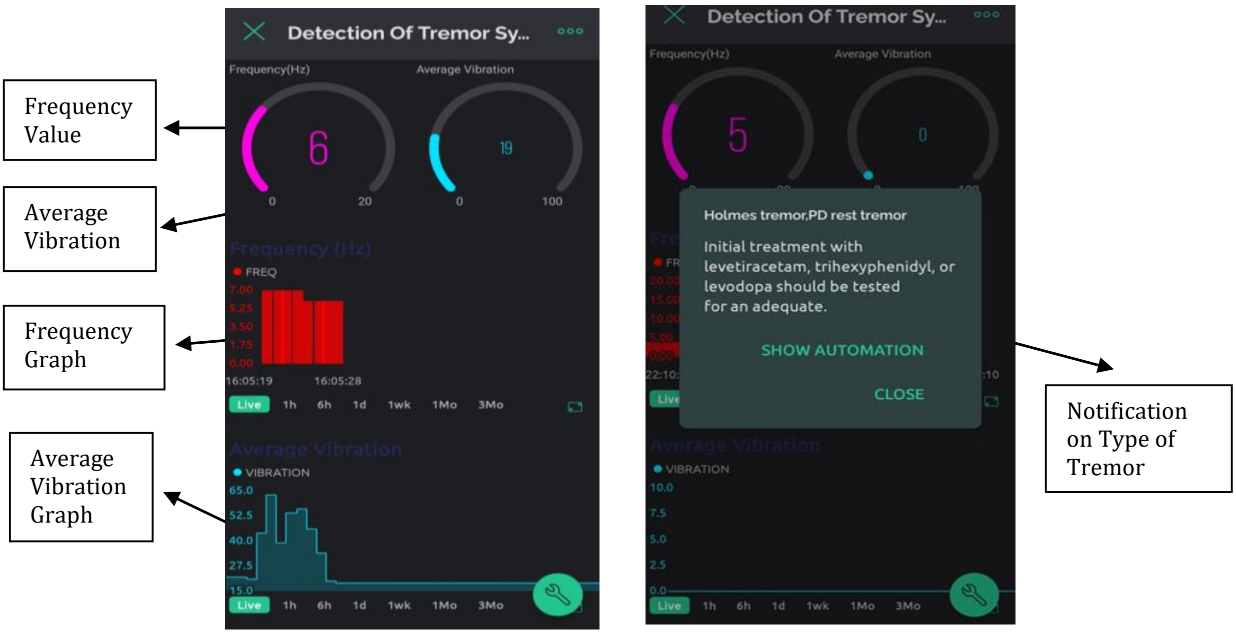

Fig. 4 *Blynk Dashboard(a)Frequency and Average Value; (b) Notification*

3.3 Result Analysis of Prototype

The testing of the model design involved the participation of five individuals who experience tremors. This group consisted of both male and female subjects who were aged 55 years and above. During the testing process, the device was held, and it accurately measured the angular velocity along the x, y, and z axes. To classify the tremors, the recorded x, y, and z values were converted into frequency using a specific formula. Based on the derived frequency values, the tremors were categorized according to their respective tremor types. shows the formula that used in coding to convert frequency (Hz) value based on accelerometer readings (m/s^2).

$$
\begin{aligned}
xx &= xx/100; \\
yy &= yy/100\,; \\
zz &= zz/100\,; \\
AVGFRQ &= (\mathrm{xx} + \mathrm{yy} + zz)/3\,;
\end{aligned}
\tag{1}
$$

The testing of the model design involved the participation of five individuals who experience tremors. This group consisted of both male and female subjects who were aged 55 years and above. During the testing process, the device was held, and it accurately measured the angular velocity along the x, y, and z axes. To classify the tremors, the recorded x, y, and z values were converted into frequency using a specific formula in Equation (1). Based on the derived frequency values, the tremors were categorized according to their respective tremor types.

Table 1 shows the result that display on Blynk mobile application based on tremor detection. The analysis result based on two data which are actual data from research paper "Approach to a tremor patient", author is S. Pandey and S. Sharma [7]. Five subject of tremor individuals with different gender were tested. The device should be on and held by the subject in order to receive the data. The Blynk application will display the value of frequency that converted from accelerometer readings. Three sample for each subject were taken to get the accurate reading. The average of tremor detection among subjects are between 2.7 Hz to 7 Hz.

By getting all results from three trial data, comparison of average collected data and actual data have been made using midpoint formula in Equation (2) and the percentage error can be determined using the formula in Equation (3). The percentage error is below 40%. From the result tremor detector device can be recommended to determine the tremor type because lowest percentage error contribute to higher accuracy.

Table 1 *Comparison of actual data and collected data*

Name & Age	Type of tremor	Range	Actual data (Hz)	Collected data (Hz)			Average of collected data (Hz)	Percentage Error (%)
Subject 1 (76)	Enchanced physiological tremor	4 - 12	$\frac{(4+12)}{2}=8$	7	4	10	7	$\frac{(8-7)}{7}\times 100$ = 14.29
Subject 2 (80)	Intention tremor	<5	$\frac{(1+4)}{2} = 2.5$	2	2	4	2.7	$\frac{(2.7-2)}{2}\times 100$ = 35
Subject 3 (53)	Holmes tremor	3 – 6	$\frac{(3+6)}{2} = 4.5$	4	6	3	4.3	$\frac{(4.5-4.3)}{4.3}\times 100$ = 4.65
Subject 4 (56)	Enchanced physiological tremor	4 - 12	$\frac{(4+12)}{2}=8$	6	4	10	6.7	$\frac{(8-6.7)}{6.7}\times 100$ = 19.4
Subject 5 (59)	Holmes tremor	3 – 6	$\frac{(3+6)}{2} = 4.5$	4	5	3	4	$\frac{(4.5-4)}{4}\times 100$ = 12.5

$$\%\mathrm{Error} = \frac{(actual\ data - collected\ data)}{collected\ data}\ X\ 100 \tag{3}$$

4. Conclusion

To sum up, the purpose of developing the tremor detector with mobile application for tremor sufferers was to increase user comfort and reduce stress. This work's goals were also accomplished with success. To identify the hand tremor, a gyro sensor with angular velocity detection is used. To determine the correlation between the frequency, range from the sensor circuit and the hand tremor, an experimental test was conducted. The outcome demonstrates that the sensor accurately determines the range of frequency and recognizes hand tremors. When comparing the average collected data with the actual data, the percentage error was less than 40%. This demonstrates that the type of hand tremor can be identified using the tremor detector device. The user can also use the Blynk mobile application to track their average tremor vibration. Additionally, the gadget converts the accelerometer readings to frequency and creates an angular velocity graph to depict hand tremor. By utilizing the Blynk app to obtain this frequency data on their smartphone, users can determine the type of tremor they are experiencing. Additionally, the app offers tailored advice based on the type of tremor, encouraging users to take preventative measures before the condition worsens. This innovative and practical approach has the potential to significantly improve tremor diagnosis and treatment, providing patients and their caregivers with greater control over their health. In conclusion, several recommendations have been proposed for future work to enhance the performance and usability of the tremor assessment system. Integrating state-of-the-art technologies, particularly sensor fusion involving pressure and accelerometer sensors, is highlighted to provide a more comprehensive analysis of tremor characteristics. The inclusion of interactive data visualization in the Blynk app is suggested to improve the user experience, allowing individuals to track tremor progress and assess the effectiveness of various treatments through interactive dashboards. Empowering users with a clear understanding of their health journey facilitates informed decision-making. Additionally, to enhance the device's usability, it is recommended to focus on increasing battery life by exploring low-power technologies and implementing energy-saving optimizations. This not only improves the device's utility but also contributes to a more user-friendly experience by reducing the frequency of recharging.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: study conception and design: Melizza Nadarajan; data collection: Melizza Nadarajan; analysis and interpretation of results: Melizza Nadarajan; draft manuscript preparation: Melizza Nadarajan, Nik Mohd Asri Nik Ismail. All authors reviewed the results and approved the final version of the manuscript.

References

[1] Smaga, S. (2003b, October 15). Tremor. AAFP. https://www.aafp.org/pubs/afp/issues/2003/1015/p1545.html
[2] Bhattacharjee, M., & Bandyopadhyay, D. (2019). *Flexible Paper Touchpad for Parkinson's Hand Tremor Detection. Sensors & Actuators:* A. Physical, 294, 164–172. https://doi.org/10.1016/j.sna.2019.05.006
[3] Shi, W. Y., & Chiao, J.-C. (2016). *Contactless hand tremor detector based on an inductive sensor*. 2016 IEEE Dallas Circuits and Systems Conference, DCAS 2016. https://doi.org/10.1109/DCAS.2016.7791147
[4] Yi, P. X., Yusof, M. M., & Chelappan, K. (2019). A Mobile-based Tremor Detector Application for Patients with Parkinson's Disease. International Journal of Advanced Computer Science and Applications, 10(7). https://doi.org/10.14569/ijacsa.2019.0100719
[5] Ibáñez, J., Serrano, J. I., del Castillo, M. D., Gallego, J. A., & Rocon, E. (2013). Online detector of movement intention based on EEG—Application in tremor patients. Biomedical Signal Processing and Control, 8(6), 822–829. https://doi.org/10.1016/j.bspc.2013.07.006
[6] De Marchis, C., Schmid, M., & Conforto, S. (2012). An optimized method for tremor detection and temporal tracking through repeated second order moment calculations on the surface EMG signal. Medical Engineering and Physics, 34(9), 1268–1277. https://doi.org/10.1016/j.medengphy.2011.12.017
[7] Sharma, S., & Pandey, S. (2016). Approach to a tremor patient. Annals of Indian Academy of Neurology, 19(4), 433. https://doi.org/10.4103/0972-2327.194409