A rest tremor detection system based on internet of thing technology

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ABSTRACT

This article outlines the creation of a health detection system designed to identify rest tremors in Parkinson's disease (PD). The system leverages internet of things (IoT) technology to measure frequencies derived from human activities, excluding other symptoms such as heartbeat and voice recording. The core components include the Arduino Nano microcontroller and the Node ESP MCU 8266 V3 for data processing. The system employs an accelerometer sensor positioned at the body's center axis to gauge the frequency of motor symptoms associated with resting tremors, particularly when the hands are at rest in the lap. The findings indicate that 9 samples displayed symptoms of rest tremor. The recorded p-value, standing at 0.884, signifies a robust correlation between the two variables at a significant threshold of 0.01 or 1%.

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1. INTRODUCTION

Parkinson's disease (PD) is a degenerative disorder that results from the loss of dopaminergic cells in the substantia nigra, a basal ganglia component situated in the brain's central region. It impacts different body areas and manifests through motor signs like tremors, akinesia, rigidity, bradikinesia, postural unpredictability and challenges in walking, and rigidity in posture. Furthermore, PD can lead to non-motor symptoms like cognitive deficiencies such as memory loss and difficulties in thinking [1]–[6]. Most individuals receive a PD diagnosis in their 70s, although 15% of cases occur in those under 50 years old. The rate of its spread is estimated over 4% for people over 65 years old [7]. Studies involving clinical and pathological analysis indicate that up to a quarter of PD patients are misdiagnosed [8]. Detecting PD remains challenging as there is currently no blood test available to definitively confirm its presence. Typically, diagnosis relies on clinical examinations and brain scans. These methods are quite expensive, occasionally inaccurate, and demand a high level of professional expertise [9], [10].

Tremor is a prominent symptom in the range of movement disorders, characterized by involuntary rhythmic movements occurring in various parts of the body such as hands, arms, head, neck, and the entire body [11]–[13]. From a clinical perspective, tremors are primarily classified into two types: rest tremor and action tremor. Rest tremor happens when the specific body part is fully supported against gravity, such as when hands are resting in the lap. The intensity of tremors increases during mental stress, like counting backwards, or during general movement, like walking, and decreases when the movement is directed towards a target, such as in the finger-to-nose test [14], [15]. In the interim, rest tremors are categorized based on factors such as their location, frequency, intensity, rhythm, the interplay between periods of rest and movement, root causes, and pathological alterations. These vibrations might manifest either on one side or both sides of the body and are commonly observed in the outermost regions of the fingers and hands. They can occur at a leisurely pace, ranging from 3 to 5 Hz, a moderate rate of 5 to 8 Hz, or an intense pace of 9 to 12 Hz. These tremors can display various characteristics, including substantial or moderate intensity, a consistent or erratic pattern, and either rhythmic or non-rhythmic nature.

The previous study, [16] categories tremor into resting, action, and intention types and responding to L-dopa treatment. Meanwhile in [17] focuses on three specific activities, postural tremor; tremor in action and rest tremor. The data were collected from the index finger of the most affected hand of five patients, both when they were medicated (ON condition) and when they were not taking medication (OFF condition). Then, [18], shows the diagnosis and evaluation are conducted by the neurologist through subjective assessment, relying on the unified Parkinson's disease rating scale (UPDRS). The UPDRS is employed to assess the patient's hand and leg movements, categorizing PD symptoms on a scale from 0 (normal) to 4 (most severe impairment). The primary gap highlighted in these sentences pertains to the absence of a thorough and consistent approach in categorizing and diagnosing PD symptoms. The earlier studies mentioned concentrated on various tremor aspects and utilized assessment methods dependent on L-dopa consumption levels. Additionally, these studies emphasized subjective evaluation based on UPDRS criteria. The lack of a unified methodology or standardization in classifying tremor types or evaluating PD symptoms results in potential inconsistencies and challenges when comparing research outcomes or establishing a universally accepted diagnostic framework.

Hence, in the face of rapid advancements, there's a demand for innovations that enhance human well-being. One such innovation involves offering complimentary healthcare services, fostering cooperation among all involved parties in healthcare, ensuring individuals can access vital services, aiding decision-making through information provision, and promoting equitable resource allocation [19]–[21]. Building on these principles, the author aims to contribute by pioneering the early detection of rest tremors in PD, facilitated through the application of internet of things (IoT) technology with measures the number of frequencies from human activities without considering other symptoms like detection from heartbeat and voice recording. The system's approach involves quantitatively assessing tremors, particularly focusing on subtle frequency variations that occur during periods of inactivity.

2. METHOD

The research follows scientific methods, employing deductive reasoning to explore specific topics specifically delves into the resting tremor type of PD. The method used is a quantitative method involving statistical techniques and sample analysis to interpret research results. These observations will then be recorded in a statistical graph. Analysis of the results begins with descriptive statistics, involving univariate measures such as frequency distribution, mean, and standard deviation, to interpret the sample data. Next, this research examines the relationship between the dependent variable (frequency value) and the independent variable which is represented on the x, y and z axes. In this experimental research, quantitative data is collected through direct frequency measurements when the body is fighting gravity [22]. The framework of the proposed prototype for early detection of rest tremor is illustrated in Figure 1.

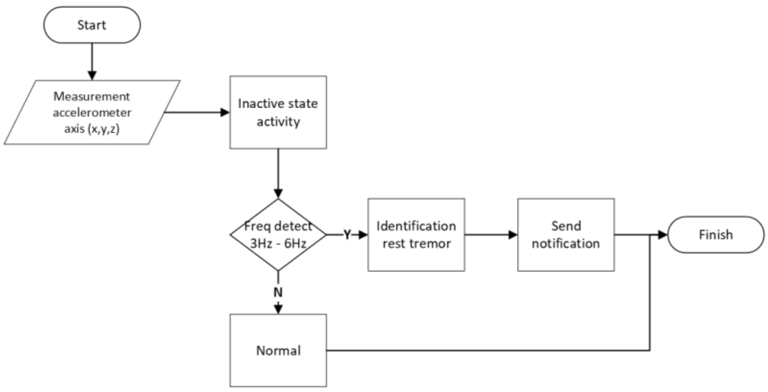


Figure 1. The workflow of rest tremor detection

The process initiates by recording data from the accelerometer sensor axis, followed by extracting relevant features and categorizing the frequency of motor symptoms related to resting tremor, specifically when the hands are at rest in the lap. Resting tremors are analyzed within the frequency range of 3 Hz to 6 Hz. If none of these specific characteristics are identified, it indicates the individual is in a normal state. The collected data is then retrieved from the sensor and presented on both the liquid crystal display (LCD) screen and mobile applications after the completion of the entire testing process.

2.1. Development methodology

This research incorporates the system development life cycle (SDLC) model and integrates it with a prototyping technique. Which includes the development of preliminary functional prototypes. The details of the prototyping model are explained further in Figure 2.

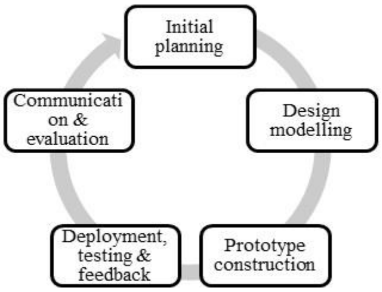


Figure 2. Prototyping model

The prototyping model outlined above elucidates several aspects pertinent to this research:

a) Initial planning: in the first phase of creating the prototype, researchers strategically plan the areas of study encompassing IoT functionalities and the specific focus within PD, particularly resting tremor.
b) Design modeling: swift design modeling is employed to outline the structure and functionality of IoT-based systems in relation to PD, serving as the core study focus.
c) Prototype construction: this stage involves the actual development and deployment of sensors tailored for detecting PD, representing a pivotal step in the research process.
d) Deployment, testing, and feedback: the prototype undergoes rigorous testing, evaluating the interaction between hardware and software, especially concerning the detection of PD in individuals. This phase also includes gathering feedback for refinement.
e) Communication and evaluation: this component gauges whether the system implementation aligns with the initial research objectives, assessing its effectiveness as perceived by relevant stakeholders.

2.2. Block diagram and hardware configuration

2.2.1. Block diagram

A graphical representation known as a block diagram illustrates the structure of a system or process. It employs labeled blocks to symbolize individual components or functions and arrows to indicate the flow or sequence between these elements. This diagram provides a comprehensive overview of the system, facilitating the understanding of its internal organization and connections [23]. A health detection system for rest tremor in PD has been developed using an accelerometer sensor called ADXL335. The system integrates IoT technology and utilizes Arduino Nano as the microcontroller, along with Node ESP MCU 8266 V3 for data processing. The system's architecture is outlined in Figure 3:

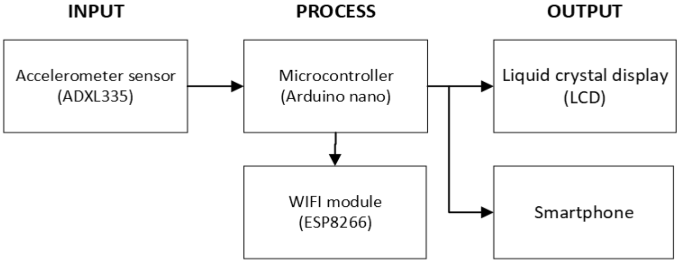
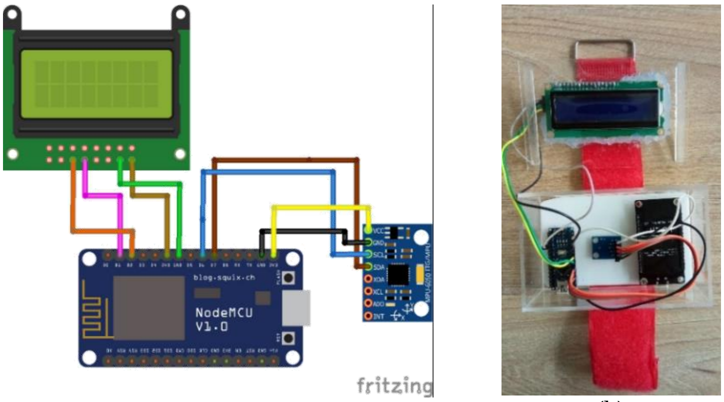


Figure 3. Block diagram of the system

2.2.2. Hardware configuration

The setup procedure begins by assembling all necessary devices (Arduino nano as microcontroller; node ESP8266 as wifi module, LCD) and connecting the integrated sensor devices to create a prototype sensor node (accelerometer sensor type ADXL355). This configuration is illustrated in Figure 4. As the detail mention in Figure 4(a) as the shecmatic diagram of the device that consist of electronic parts and Figure 4(b) the details of the devices.

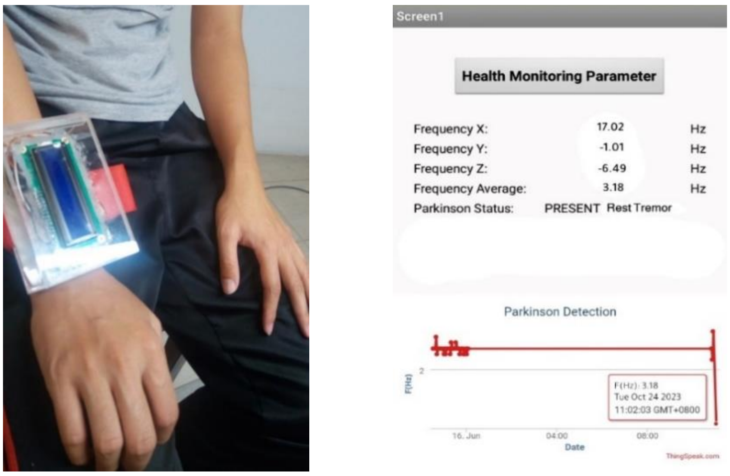


(a) (b)

Figure 4. Hardware configuration (a) schematic diagram and (b) internal part

2.3. Experimental method

The experimental design entails a quantitative research approach aimed at investigating the impact of an experimental group, represented by independent variables, on the outcomes of a control group, represented by dependent variables. This investigation involves the collection of randomly gathered data from 25 participants, wherein the sensor is positioned on the wrist area. Participants will be requested to maintain stillness while seated and put the hands are at rest in the lap, aiming to identify the frequency of vibrations related to PD, specifically a form of tremor that occurs during rest displayed in Figure 5. This assessment will encompass a duration of approximately 15 seconds during a single test. Should participants exhibit symptoms of rest tremors, they will manifest movements within their hands and fingers like illustrated in Figure 5(a). The detection frequency will be categorized into mild, ranging from 3 Hz to 3.5 Hz, moderate, spanning from 3.6 Hz to 4.0 Hz, and severe, covering 4.1 Hz to 6 Hz. Upon the conclusion of the testing process, all gathered sample data will be stored in Thing Speak before being visually represented in graphical format on a smartphone like ilustrated in Figure 5(b).



(a) (b)

Figure 5. Experimental method (a) rest tremor test and (b) result of experimental method

3. RESULTS AND DISCUSSION

In this segment, we presented the outcomes of the experimental analysis. The objective of evaluating the system's detection capabilities, developed through proteus simulation software [24], [25], is to ascertain the correlation within an electronic circuit. This analysis employs quantitative research methods, encompassing descriptive statistics. To validate the findings, Pearson correlation and multiple linear regression tests were conducted to identify the relationship between independent and dependent variables. After the completion of these assessments, it was determined that 9 samples displayed indications of motoric tremors associated with rest tremor in PD. The frequency values for these samples are detailed in Table 1:

Table 1. Rest tremor result

Sample participant	Average frequency
S1	3.18 Hz
S10	3.24 Hz
S14	5.17 Hz
S17	5.15 Hz
S19	5.93 Hz
S20	3.32 Hz
S21	4.59 Hz
S22	3.10 Hz
S23	3.26 Hz

The initial phase of the simulation process for evaluating electronic circuits associated with symptoms of resting motoric tremors entails acquiring a file bearing the .HEX extension. Subsequently, this file is imported into the proteus simulation software, serving the purpose of validating the seamless functionality of all circuits and the identification of potential errors through functional testing. The simulation is executed as a singular phase under the complete control of the Arduino Nano. It initiates by emulating the function of an accelerometer sensor through the utilization of a voltage divider circuit constructed with three resistors. These resistors substitute the sensor's x, y, and z axes as depicted in Figure 6. Subsequently, the voltage measurement needs to be input as digital data into the Arduino Nano microcontroller. The analog pin on the Arduino Nano encompasses a scale spanning from 0 to 1023, where 0 symbolizes a voltage of 0 volts and 1023 signifies a voltage of 5 volts. Through the process of converting analog input readings into digital data, the initial resistor is linked to pin A0, followed by the second and third resistors, which are linked to pins A1 and A2. During a state of rest, the assessment of movements commences within a frequency spectrum of 3 Hz to 6 Hz. The outcomes of these tests are then transmitted to the LCD.

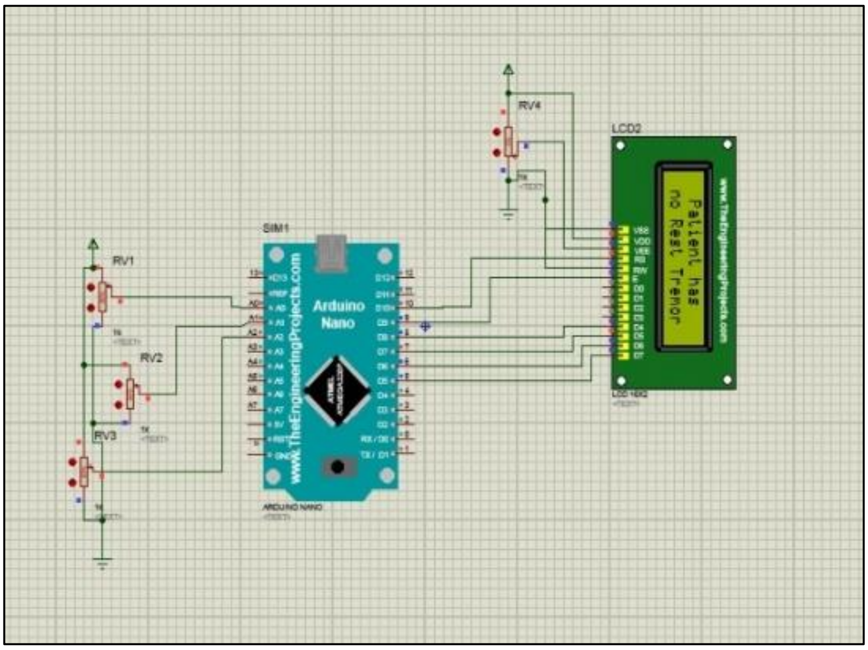


Figure 6. Rest tremor simulation

3.1. Validity analysis

In this research, the validity assessment was conducted through the utilization of Pearson's correlation test, which aims to quantify the level of proximity between the variables. The fixed coefficients are set at values of -1 and 1. It is a numerical value ranging from -1 to 1, indicating both the intensity and direction of the connection between two variables. There are three fundamental guidelines for making decisions in this Pearson correlation analysis. Firstly, it involves examining the Sig (2-tailed) value and comparing it to an alpha value of 0.05. If the Sig (2-tailed) value is less than 0.05, it indicates a correlation between variables; conversely, if the Sig (2-tailed) value exceeds 0.05, there is no correlation. Secondly, it considers whether the r-count value is greater than the r-table value, signifying a correlation between variables, or if r-count is less than r-table, indicating no correlation between variables. Thirdly, it assesses the presence of asterisks (*) or (**) on the Pearson correlation value. The significance of these two asterisks is as follows: the single asterisk (*) signifies a correlation at a 1% or 0.01 significance level, whereas the double asterisks (**) represent a correlation at a 5% or 0.05 significance level [26]. The outcomes of the resting motor tremor examination are presented in Table 2, showcasing the results obtained from the SPSS analysis.

Table 2. Correlation of rest tremor detection

Correlations

		x-axis	y-axis	z-axis	frequency
x-axis	Pearson correlation	1	-.476*	-.046	.345
	Sig. (2-tailed)		.016	.826	.091
	N	25	25	25	25
y-axis	Pearson correlation	-.476*	1	.111	.145
	Sig. (2-tailed)	.016		.597	.489
	N	25	25	25	25
z-axis	Pearson correlation	-.046	.111	1	.884**
	Sig. (2-tailed)	.826	.597		.000
	N	25	25	25	25
frequency	Pearson correlation	.345	.145	.884**	1
	Sig. (2-tailed)	.091	.489	.000	
	N	25	25	25	25

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

Referring to the three conditions mentioned earlier, the validity test results for PD with rest tremor symptoms, as presented in Table 2, can be summarized as follows:

a) The sig value (2-tailed) between the z-axis value and the average frequency value is 0.000. This indicates a significant correlation between the changes in the z-axis value and the average frequency.
b) For this data analysis, the r-table is 0.396. In contrast, the r-count for the relationship between the z-axis value and the average frequency value is 0.884. It can be concluded that the R-value for each criterion is greater than the r-table, indicating a correlation between the z-axis values and the average frequency.
c) The R-value for each criterion is larger than the r-table, indicating a correlation between the z-axis values and the average frequency.
d) The z-axis value with the average frequency is denoted by (**) signifying a correlation at the 0.01 significance level or 1%. This significance represents the crucial point at which the outcomes of a statistical test are deemed noteworthy. Put simply, if the p-value (probability value) derived from the test is equal to or less than 0.01, it suggests a highly improbable occurrence (1%) of the observed results happening solely by chance. This threshold is selected to guarantee a strong level of confidence in the research outcomes.

3.2. Coefficients determination

The coefficient of determination assesses the regression model's capability to account for the fluctuations in the dependent variable. Conversely, as seen in Table 3, the adjusted R-squared coefficient of determination stands at 99.8%. This signifies that the changes observed in the dependent variable of frequencies can be attributed to a high degree to the independent variables (x, y, z axis).

Table 3. Coefficient determination

Model summary

Model	R	R square	Adjusted R square	Std. error of the estimate
1	.999a	.998	.998	.08563

a. Predictors: (Constant), z-axis, x-axis, y-axis

3.3. ANOVA test

An analysis of variance (ANOVA) test was conducted to assess whether the combined independent variables had a significant impact on the dependent variable. This study aimed to determine if the variables on the x, y, and z axis significantly influenced the frequency variable. Initially, the significance value (Sig) or the probability value of the ANOVA output was compared. If Sig. <0.05, it indicated that the values on the x, y, and z axis collectively influenced the frequency value. Conversely, if Sig. >0.05, it meant that the values on the x, y, and z axis had no simultaneous effect on the frequency value. Subsequently, during the ANOVA test, the degree of freedom (df) is calculated as shown in (1):

$$df = n - (k + 1) \tag{1}$$

Here, "n" represents the count of respondents or research participants, while "k" stands for the number of independent variables. In the present study, "k" equals 3, signifying the variables x, y, and z, while the value of "n" is 25 samples. As shown in Table 4, the F value is recorded as 917.213, and the significance value (Sig.) is noted as 0.000.

Table 4. ANOVA result test

	Model	Sum of squares	df	Mean square	F	Sig.
1	Regression	33.609	3	11.203	917.123	.000[a]
	Residual	.134	11	.012		
	Total	33.743	14			

a. Predictors: (Constant), z-axis, x-axis, y-axis

b. Dependent Variable: frequency

4. CONCLUSION

A novel iteration of a rest tremor detection system was introduced. This system was constructed utilizing components like an accelerometer sensor, an ESP8266 wifi module (node), an LCD, and a smartphone. It is designed to identify periods of inactivity following 15 seconds of seated positioning. From the test outcomes, it was determined that 9 samples exhibited symptoms of Parkinson's rest tremor. The recorded p-value was 0.884, indicating a strong correlation between two variables at a significant threshold of 0.01 or 1%. The adjusted R-squared value, standing at 99.8%, signifies that the dependent variable is largely represented by the independent variable, with only 0.2% influenced by other parameters not accounted for in this study. Furthermore, during the ANOVA test, with 25 samples and 3 degrees of freedom, the F-values were measured at 917.123, accompanied by a significance value of 0.000.

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