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# Utilizing Flex Sensors for the Evaluation of Parkinson's Disease

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***Abstract*—Parkinson's disease is a neurodegenerative disorder with symptoms such as tremors, stiffness, and issues with balance and coordination. Detecting and monitoring the signs of the disease is of great significance. By combining flex sensors and Arduino, we have designed a simple and effective system capable of recording, detecting, and evaluating early signs of the disease. The electronic components used are: an Arduino Nano, two flex sensors, and a glove with sensors attached to each finger to capture movements and flexion. The patient wears the glove and whenever tremors are detected, the sensor sends a signal to the Arduino which is converted into an angle of flexion by changing resistance. The tremor signals are initially transmitted as resistance and subsequently transformed into voltage. This voltage is then graphed according to the sensor's bending angle. By analyzing abrupt and rapid tremors, a threshold is established to deduce the severity and progression stage of the illness.**

***Index Terms*—Flex Sensor, Glove, Microcontroller, Parkinson’s Disease.**

## I. Introduction

Parkinson's disease is a gradual deterioration of the nervous system resulting in involuntary and unmanageable movements, including tremors, rigidity, and challenges with balance and coordination. It ranks as the second most prevalent neurodegenerative condition, impacting 2-3% of individuals aged 65 and above [2]. Symptoms typically start gradually and worsen over time. The impact of this condition can be minimized through early diagnosis and appropriate symptom monitoring, improving the management and medical treatment, and enhancing the quality of life for patients. However, detecting Parkinson's disease in its early stages often presents many challenges [26].

The tremor manifestations observed in Parkinson's disease may impact a specific region of the body (rest tremor), multiple adjacent areas (segmental tremor), one side of the body (hemitremor), or the entire body (generalized tremor). Typically, two categories of tremors are recognized based on the circumstances that elicit them: resting tremor, occurring when the affected body part is at rest, and action tremor (which includes kinetic, postural, or isometric tremor), arising when the individual initiates voluntary movements or sustains a particular posture against gravitational forces. Tremor characteristics include frequency (typically between 4-8 Hz) and amplitude. In theory, EMG is a gold standard for assessing and monitoring tremors. However, the drawback of EMG is its lack of suitability for continuous monitoring and frequent evaluation of tremor features. With technological advancements, various solutions have been proposed to enable continuous monitoring of disease symptoms and important signs. Published studies are usually focused on wearable devices [19], to provide patients with the ability to perform activities of daily living, and therefore to analyze the extent of their disease without the supervision of a doctor in a laboratory, It can be classified into two main groups: (1) devices that assess tremor features, and (2) devices that monitor tremors and the effectiveness of therapies.

Equipment designed to assess and delineate tremor attributes have demonstrated notable efficacy in clinical settings, particularly in the evaluation, diagnosis, and management of tremors associated with Parkinson's disease (PD). Subsequently, alternative wrist or forearm devices were introduced to evaluate rest and action tremors (postural and movement) in individuals with Parkinson's disease (PD) using inertial measurement units (IMUs), which include three-axis accelerometers and three-axis gyroscopes, or a combination of four three-axis accelerometers. Hssayeni et al. [16] utilized an IMU to assess tremor severity in PD, while Mahadevan et al. [22] and Dai et al. [5] employed it to distinguish between bradykinesia and tremors. Shawen et al. [31] compared the efficacy of smartwatches and skin-mounted IMUs in categorizing tremor and bradykinesia severity in PD, demonstrating that smartwatches can perform comparably to specialized sensors. Additionally, Huo et al. [15] introduced a more intricate array of devices comprising force sensors, three IMUs, and four custom mechanical sensors (MMG). These wearable solutions can accurately estimate tremor frequency and amplitude, laying the groundwork for the advancement of more sophisticated diagnostic and therapeutic monitoring devices for tremor disorders.

Continuous monitoring of tremors and evaluating the effectiveness of such monitoring are essential requirements for home healthcare solutions and intelligent services aiming to

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alleviate the strain on the National Healthcare System. Battista and Romaniello [3] introduced and validated a device akin to a smartwatch, utilizing a three-axis accelerometer, capable of identifying tremor events by computing statistical indices indicative of motion patterns. San-Segundo and Luis Sigcha [32],[20] employed a wrist-worn accelerometer paired with a smartphone annotation app to gather labeled data in controlled laboratory settings and weakly labeled data during everyday activities. Various AI models have been applied to discern tremor presence and severity from diverse feature sets [10]. However, a key challenge lies in accurately distinguishing tremors from other motions or objects due to the substantial signal variability inherent in normal daily activities. These monitoring devices exhibit improved performance when complemented with self-annotation. Nonetheless, achieving high accuracy in identifying tremors and evaluating their severity during continuous, fully automated monitoring remains an ongoing challenge.

The majority of the proposed systems utilize inertial measurement devices (IMU), including accelerometers, gyroscopes, and surface electromyography, either independently or in conjunction in certain wearable configurations [9]. Additionally, speech analysis [1, 28] serves as another significant diagnostic tool. A novel postural estimation method, integrating Transformers with HRNe, employing machine learning techniques, has been suggested [4]. Furthermore, in [8], the authors introduced a device for tracking motion trajectory and tremor occurrences. This study proposes the utilization of a magnetic tracking system to capture data on translational movements and vibrations within a spatial cubic domain.

With the two device groups mentioned above, we found that the design and use of sensor components are complex. Therefore, in this study, we used a smart glove designed as follows: a glove with two fixed bend sensors on two fingers, used to detect abnormal movements related to motor disorders and record detections [27]. The vibrations in the fingers [29] cause changes in the shape and curvature of the sensors, resulting in resistance changes. These changes are recorded and converted into voltage [12]. Then, the voltage is sent to the Arduino input and plotted against angles. The values obtained from the glove can be used for both detection purposes and for patients recovering function [26], [34].

When designing gloves, it is important that they are both aesthetically pleasing and easy to use, allowing for easy and simple manipulation [14], [19]. During the preliminary phase, the suggested system will undergo simulation using the Proteus Simulation Tool. The system comprises two primary modules: hardware and software. The hardware component encompasses an Arduino Nano, flex sensor, amplifier module, accelerometer, and Wi-Fi. Integration of both software and hardware is achieved through the utilization of embedded C language.

## II. METHOD

### A. Glove

The study used gloves made from synthetic fibers. The gloves were cut to remove three fingers, leaving only the index and middle fingers. flex sensors were placed on the outer surface of the glove, above the two fingers, and sewn into it to ensure accurate reading results [6], [24]. The amplification circuit and Arduino are fixed on the back of the hand. Below is the amplification circuit, and above is the Arduino. The output signal of the Arduino is stored in a micro SD card and transmitted to a laptop port via a cable. This is designed to minimize any potential hardware interference with the dexterity and natural movement of the user's hand. Therefore, whenever a finger vibrates or moves, it leads to a change in the resistance of the sensor.

The structure of the glove is shown above. The components will be connected as follows. One end of the sensor is grounded, while the other end is connected to a 3.3V source through a 10 kΩ pull-up resistor as shown in Fig. 1. The low voltage on the sensor is the input to the amplification circuit. The output of the amplification circuit is sent to the Arduino. After being processed on Arduino, the signal will be saved to the micro SD card and displayed on the laptop through the IDE interface.

This design enables the recording of any changes in resistance in response to alterations in the curvature or shape of the sensor [12]. The variation in resistance results in a shift in the voltage drop across the sensor. This voltage alteration is then routed through an amplification circuit, which serves as a receiver circuit, and the output voltage values are delivered to Arduino pins 5 and 7 [7]. Consequently, any movement within the glove's finger leads to a voltage change that is transmitted to the Arduino.

#### 1) *Flex sensor*

The Flex sensor is based on carbon resistive elements and is a type of sensor used to measure bending or deflection. When the sensor is deformed or bent, the resistance of the carbon material changes, and this value can be read [13], [34], [24], [17]. The resistance in this device changes linearly with the bending angle. Therefore, the flex sensor can be used as an input signal generator for devices. The required voltage to detect normal values falls within the range of a DC current of 3.3-5V. The observed resistance change is greater when the bending angle is larger [11].

In reality, Flex sensors often produce different results, so they need to be calibrated before use. To determine the relationship between the curvature of the sensor and the change in resistance value, a test was set up. Successive sensors had flat resistance values of 12.5 kΩ and 11.8 kΩ. The resistance values were 63.51 kΩ and 56.8 kΩ when bent at 180°. When the Flex sensor is bent, the resistance increases linearly, resulting in a corresponding change in output voltage. By describing this relationship, we can use the flexible sensor to determine the movement of an individual's finger in different hand motions. Two flex sensors were used in this study, with each sensor having a linear resistance value but different flat resistance values.

#### 2) *Signal amplifier circuit*

The voltage divider circuit is utilized to convert angle measurements into voltage. The bending of the flex sensor causes a change in resistance, resulting in a corresponding change in voltage output. Arduino board provides a 3.3V power supply voltage through a pull-up resistor $(R_M)$, which is then connected to the nominal resistance ( $R_{flex}$ ) of the flex sensor. One end of the flex sensor is grounded, and the output voltage (Vout) is measured across it. We can determine the relationship between the voltage on the flex sensor and the output voltage by using the voltage division formula [7]. The output voltage measured on the flex sensor is determined by the following formula (1).

$$V_{in} = \frac{R_{flex}}{R_M + R_{flex}} \times Vcc \tag{1}$$

In Fig. 1, when the flex sensor is flat, the output voltage Vin is 1.75V when Vcc = 3.3V, $R_M = R_{flex} = R$. To determine the output voltage level, the nominal value of the sensor can be calculated using formula (1). From this, it can be observed that the greater the output voltage, the more the flex sensor bends.

To ensure a stable input signal to the Arduino, we employ an additional module that functions as an amplifier and buffer before transmitting the signal to an Arduino pin. The output voltage will be converted to a digital signal by sending a value to the analog pin of the Arduino. In Fig. 1, the relationship between input and output will be calculated using the following formula (2):

$$Vout = (1 + \frac{R_1}{R_2 + R_3}) \times Vin \tag{2}$$

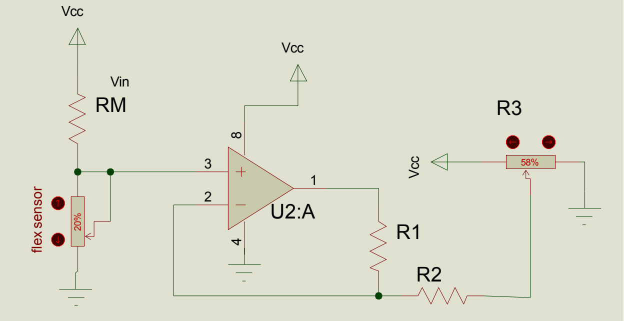


Fig. 1 Signal amplifier circuit.

In addition, we have also designed a module to store data on a micro SD card. This data will be convenient for analysis and evaluation. The gloves are designed with the described components and will function according to the diagram shown in Fig. 2.

### B. Experimental Procedure

The movement of the hand is a complex motion that encompasses the wrist, hand, and fingers. Various quantities describe this motion, as illustrated in Fig. 3. In Fig. 3-a, α represents the rotation angle of the hand, 3a ,β is the angle of motion of the wrist, and 3c $\theta_j^i$ is the angle of motion of the finger relative to the hand, where i has symbols from 1 to 5 corresponding to the fingers, j is the angle of the knuckles from 1 to 3, respectively.

The first step in study, our focus is solely on the finger's motion ( $\theta_3^i$ angle) relative to the hand. This motion is considered a change in angle, as depicted in Fig. 3c.

The data collection process is as follows: The test subject wears gloves and performs movements with their hand and individual fingers. The resulting output is interpreted as changes in voltage and recorded. Each sensor has a different initial value based on the stiffness of the material and the angle of deviation, so not all initial voltage values are the same.

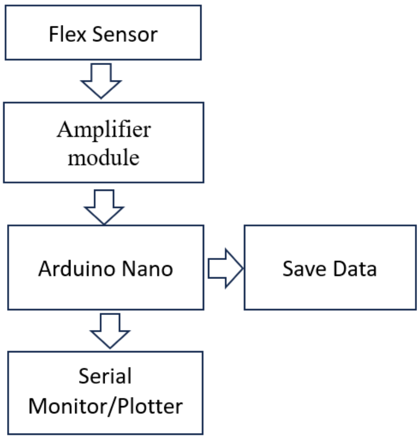


Fig. 2 Flowchart depicting workflow.

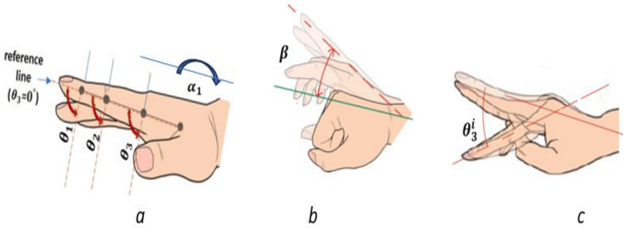


Fig.3 a- The angle of movement of the hand; b- the angle of motion of the hand relative to the forearm; c- the angle of movement of the finger relative to the hand, with i from Eq. 1-2.

The initial position is defined as follows: the gloved hand is placed on a flat surface, with the fingers extended straight and parallel to the hand at an angle (Fig. 4). To observe the glove's response, perform the following actions: gradually bend and tighten the fingers to 180°, then straighten the fingers back to their initial position. The voltage output should fall within the range of 2.2-3.3V. The hand should be held steady with the fingers straightened, gradually bent, and tightened, as shown in Fig. 3b. These movements will determine the output limits of the corresponding signal value. The output signal is then adjusted to fall within the desired range. Multiple repeated measurements are conducted to analyze the sensitivity of the flex sensor [11]. Collect data with the following motions.

- Collect data with a small angle $\theta_3^i < 45^o$ : keep your hand steady, move your fingers with different amplitudes and frequencies.
- Collect data with a large angle ( $45^o < \theta_3^i < 90^o$ ) keep your hand steady, vibrate your fingers with a small amplitude and frequency.

The voltage graph recorded from the index finger and middle finger is approximately 2.25V in the initial established state $\theta_3^i = 41^o$ . In this experiment, the angles $(\theta_3^i)$ were primarily measured from 0° to 90°. The chart illustrates the voltage change when the sensor is bent, as shown in Fig. 6. To test the sensitivity of the device, record the voltage change when the finger vibrates at different speeds, ranging from low to high.

The second step, register the signal of hand vibration with $\alpha \neq 0$. In this position the hand will place parallel to the tabletop, as depicted in Figure 3c.

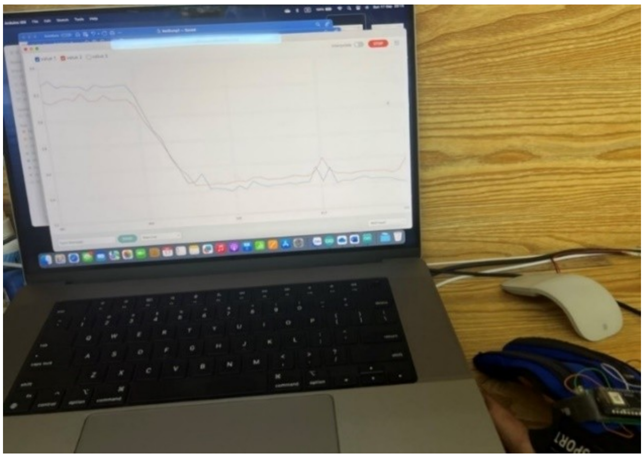
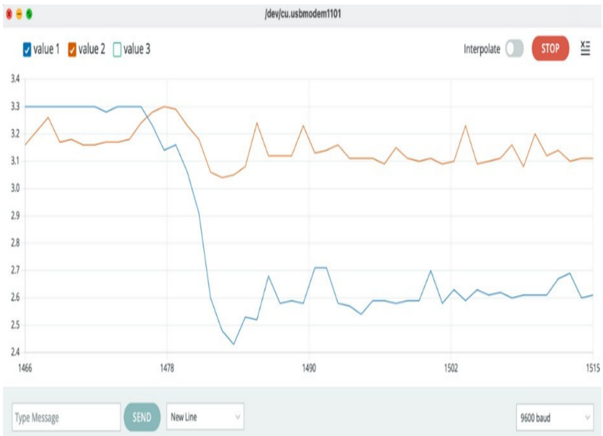


Fig.4 Shows the initial state of the test.



/dev/cu.usbmodem1101

☑ value 1 ☑ value 2 ☐ value 3

Fig. 5 Demonstrates the voltage changes as the finger moves at different angles.

## III. Results and Discussion

The change in voltage over time is depicted in the graph below (Fig. 6). When the finger is held in a fixed position, the voltage change is insignificant. For example, $\theta_3^1 :\ 20^o$, $\theta_3^2 :\ 90^o$ as shown in Fig. 5, the voltage remains relatively constant. However, when gripping, there is a peak on the chart, with the voltage reaching a maximum value of 3.3V. In Fig. 6, Series 1 and Series 2 represent data collected from the index finger and middle finger, respectively. Small, insignificant changes in the graph indicate minor alterations in finger movement. The voltage is measured based on angles ranging from 0° (flat surface) to approximately 120° (excluding the first fully tightened position). The angles increase gradually from 0° to 90°. This is done to test sensitivity, accuracy, and perform calibration to assess the device's stability. The device's stability enables us to detect subtle vibrations on the finger. The graphs below illustrate the relationship between voltage and flex angle. In Figs. 7 and 8, the graphs display voltage variations when the flex angle is less than 45° and greater than 45°, respectively.

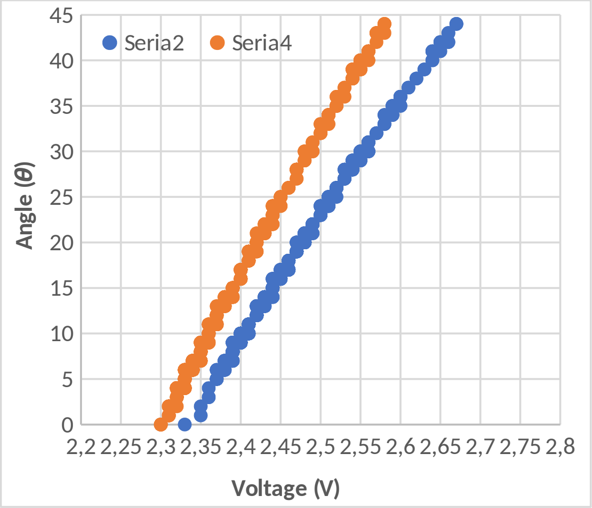


Fig. 6 Shows the relationship between voltage and flex angle

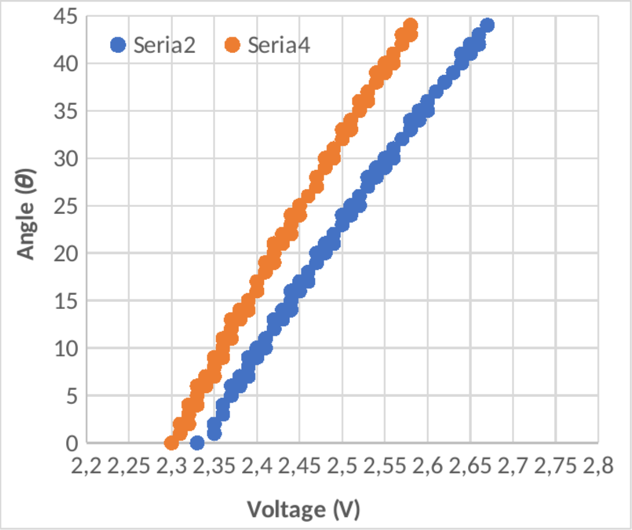


Fig. 7 Voltage and angle of lex when $\theta_3^i$ <45°.

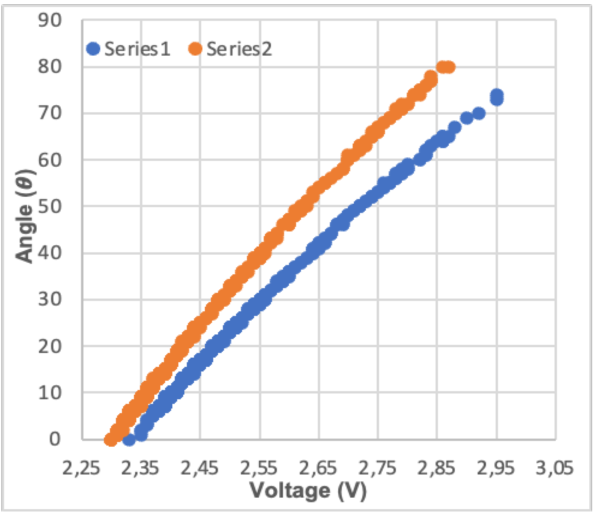


Fig. 8 Voltage and angle of lex when $\theta_3^i$ <90°

Using the formula, we will calculate the resistance value R3 for calibration with voltage input into Arduino. It can be observed from the graph above that the voltage changes linearly with the angle. This demonstrates that when the fist is clenched, the voltage undergoes significant changes in small increments. This device model can be utilized for individuals with Parkinson's disease. Additionally, the device is capable of detecting and evaluating the early stages of Parkinson's disease.

## IV. Conclusion

Parkinson's disease is a condition of the nervous system that leads to involuntary or uncontrollable movements, including tremors, stiffness, and issues with balance and coordination. Typically, symptoms start off mild and worsen over time. As the condition progresses, people may have difficulty speaking and moving. This study primarily focuses on Parkinson's patients who are currently affected by the disease or experiencing early symptoms. The goal is to develop a reliable testing and diagnostic method that allows us to classify the signs and symptoms of the disease. The study also aims to make automatic monitoring and severity assessment easier. The flex sensors and Arduino Nano controller have been successfully integrated into the electronic glove system. Each component works well and provides accurate data from the flex sensors. This system has the advantages of affordability, minimal parts with small size, quick response, reliability, and easy management. There was a slight variation in angles during the repeatability testing process, but the project's objective has been achieved. This is demonstrated by the linear transformation of voltage and resistance when detecting vibrations using 2 flex sensors. This model can be used to detect early signs as well as monitor and assess the condition of Parkinson's disease. This study has focused on developing an electronic glove system that effectively detects and monitors the symptoms of Parkinson's disease, with a particular emphasis on early detection. The successful integration of the flex sensor into the wearable device has delivered a cost-effective, compact, and reliable solution for this purpose. In the future, we tend to develop embedded algorithms on wearable devices [6], [18], [21] [23], [25], [35], [36] integrated with constrained-performance microcontrollers to analyze the complex variations of Parkinson's patients in various postures and intricate actions in daily life.

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