Dynamic Spoon Positioning for Parkinson's Patients and Disease Stage Prediction

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***Abstract*—This work presents an advanced sensor-based predictive modeling approach for dynamic spoon positioning and Parkinson's disease stage prediction. Parkinson's disease is a progressive disorder that affects the nervous system and the parts of the body controlled by the nerves. This affects motor function causing tremors, rigidity and slowness of movements and impact day to day activities such as eating. Traditionally, Parkinson disease depend on clinical evaluation which have to be done frequently. Our dynamic spoon not only stabilize the food but also monitoring patient condition. This project proposes modern method to stabilize smart spoon using not only sensor input but also machine learning technique to increase the stability. Furthermore, machine learning techniques are used to train predictive models capable of accurately predicting spoon positioning and Parkinson's disease stage. This design aims to provide real time feedback to the guardian or Doctor, accessing early detection of Parkinson disease and monitoring progression and stages. This improves patients' quality of life and healthcare outcomes.** ***Index Terms*—self-stabilizing, Machine learning techniques, Real-time feedback**

I. Introduction

Parkinson's disease (PD) is a progressive neurological disorder that affects movement. It is characterized by symptoms such as tremors, stiffness, bradykinesia (slowness of movement), and postural instability. While Parkinson's is often associated with older individuals, it can affect people of all ages, with only a small percentage diagnosed before the age of 50. [1] According to statistics, approximately 4% of all cases occur in individuals under the age of 50, making it more prevalent in older populations. As the second most age-related nerve degeneration disorder after Alzheimer's, Parkinson's poses significant challenges to individuals and their guardians.

The prevalence of Parkinson's disease increases with age, with the majority of cases diagnosed in individuals over 60 years old. However, it's important to note that PD can also affect younger individuals, albeit less frequently. The impact of Parkinson's on daily life can be unpleasant, affecting various aspects of functioning, including mobility, communication, and independence. With the aging population worldwide, the burden of Parkinson's disease is expected to rise, necessitating innovative solutions to improve the quality of life for affected individuals.

One of the primary challenges faced by individuals with Parkinson's disease is the lack of fine motor skills, particularly during activities such as eating. Tremors and slowness of motion can make it difficult to control utensils and perform basic tasks independently. While assistive devices like self-stabilizing spoons exist, they may not fully address the needs of Parkinson's patients. Additionally, the high cost of existing solutions limits accessibility for many individuals, highlighting the need for more affordable and effective alternatives.

The development of a dynamic spoon positioning system aims to enhance the quality of life for individuals living with Parkinson's disease. By providing a solution that effectively addresses the challenges of tremors and motor impairments while eating, this innovative technology can empower patients to regain independence and dignity in their daily lives. With improved ability to feed themselves without assistance, Parkinson's patients can experience greater independence and confidence, leading to enhanced overall well-being.

Self-stabilizing spoons equipped with servo motors represent a significant advancement in assistive technology for Parkinson's patients. These spoons utilize sensors to detect hand tremors and adjust spoon position in real-time, allowing for more controlled and efficient eating movements. However, there is still room for improvement in optimizing the performance of these devices to better meet the individualized needs of users. Integrating machine learning models into the spoon's functionality offers the potential to predict the progression of Parkinson's disease stages and adjust the spoon's stabilization mechanism accordingly.

Machine learning algorithms can analyze sensor data collected from the spoon while eating to identify patterns indicative of Parkinson's disease progression. By monitoring changes in motor symptoms over time, the system can predict the stage of the disease and adapt the spoon's positioning to accommodate evolving needs. This personalized approach ensures that individuals receive optimal support tailored to their specific condition, enhancing the effectiveness of the assistive device in improving eating experiences for Parkinson's patients. Not only predict the stage but also monitor the progress after taking medicine.

By incorporating predictive modeling into the dynamic spoon positioning system, we can revolutionize the way Parkinson's disease is managed and treated. Not only does this technology provide real-time assistance while eating, but it also offers valuable insights into disease progression, allowing for practical Solutions and personalized care strategies. By empowering individuals with Parkinson's disease to maintain independence and Self-respect in their daily activities, this innovative solution has the potential to significantly enhance their quality of life and well-being.

The development of a dynamic spoon positioning system represents a Favorable step forward in the management of Parkinson's disease. By combining sensor technology, servo motors, and machine learning algorithms, this innovative solution offers personalized support to individuals with tremors and motor impairments, enabling them to eat more comfortably and independently. With the potential to predict disease progression and adapt in real-time, the dynamic spoon positioning system holds great promise for improving the lives of Parkinson's patients and their guardians. One such feature is the inclusion of an alert system that triggers in the event of a malfunction or if the patient stops responding. If the spoon drops or encounters an issue, it will automatically send a notification to the guardian, ensuring assistance and intervention when needed. This proactive approach not only improves safety but also provides reassurance to patients and their loved ones, allowing them to confidently rely on the technology for daily support.

In the end, a method is to be innovated to stabilize the spoon even in the presence of tremors, ensuring that the food remains stable. An IoT system is to be built to remotely monitor patient conditions while eating. Additionally, the prediction of Parkinson's disease stages should be possible.

II. System Implementation

A. Overall view of the System

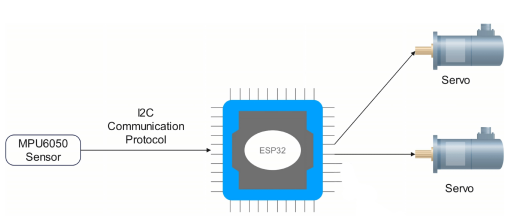

Fig. 1. System Outline

The system comprises an MPU6050 sensor, which includes an accelerometer and gyroscope, designed to detect hand movements indicative of Parkinson's disease and track orientation relative to gravity. An Atmega328P serves as the microcontroller for processing data and making decisions, subsequently transmitting the information to two servo motors. Illustrated in the above figure, the project's operational concept initiates with input from the MPU6050 sensor, which reads data upon tilting. This data is then forwarded for processing by the microcontroller, directing the servo motors to stabilize the assistive device, thereby functioning as its output.

B. Basic Working Principle

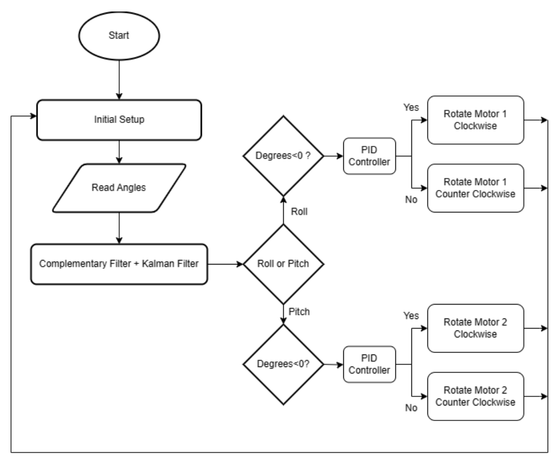

Fig. 2. Functionality of the system

With regard to the diagram above, the system's functionality can be outlined as follows. Initially, the system undergoes an initial setup phase before repetitively reading angle values. These values are then processed through complementary and Kalman filters to reduce noise and fuse data. The filtered angle data is then analyzed to discern whether it indicates a roll or pitch movement. Based on this information, the system determines the direction of motion, whether it is left or right, upward or downward. Depending on the type of movement and the magnitude of the angle value, the system decides to rotate either Motor 1 or Motor 2 clockwise or counterclockwise, ensuring that the spoon remains horizontal at all times. Without a PID controller, the spoon may struggle to effectively regulate its output to achieve the horizontal set point. To avoid these scenarios, PID controllers are used for both the X and Y axes.

C. Equations

The PID control formula:

$$\mathrm{PID}(t) = K_p \cdot e(t) + K_i \cdot \int_0^t e(\tau)d\tau + K_d \cdot \frac{de(t)}{dt} \tag{1}$$

where:

K_p: Proportional gain,

K_i: Integral gain,

K_d: Derivative gain,

$e(t)$: Error at time t,

$\int_0^t e(\tau)d\tau$: Integral of the error from 0 to t,

$\frac{de(t)}{dt}$: Derivative of the error with respect to time.

The Kalman filter formulas:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k \tag{2}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{3}$$

The update step of the Kalman filter is given by:

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \tag{4}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H_k \hat{x}_{k|k-1}) \tag{5}$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \tag{6}$$

Where:

- $\hat{x}_{k|k-1}$ is the predicted state estimate at time k given measurements up to time $k-1$.
- $P_{k|k-1}$ is the predicted state covariance at time k given measurements up to time $k-1$.
- F_k is the state transition model matrix for time step k.
- B_k is the control input model matrix for time step k.
- u_k is the control input at time step k.
- Q_k is the covariance matrix for the process noise at time step k.
- K_k is the Kalman gain at time step k.
- H_k is the measurement model matrix for time step k.
- R_k is the covariance matrix for the measurement noise at time step k.
- $\hat{x}_{k|k}$ is the updated state estimate at time k given measurements up to time k.
- z_k is the measurement at time step k.
- I is the identity matrix.

The complementary filter formula:

$$\theta_{\text{comp}}(t) = \alpha \cdot \theta_{\text{gyro}}(t) + (1-\alpha) \cdot \theta_{\text{acc}}(t) \tag{7}$$

where:

- $\theta_{\text{comp}}(t)$ is the estimated orientation at time t using the complementary filter.
- $\theta_{\text{gyro}}(t)$ is the orientation estimate from the gyroscope at time t.
- $\theta_{\text{acc}}(t)$ is the orientation estimate from the accelerometer at time t.
- α is the filter coefficient, usually chosen between 0 and 1 to control the contribution of each sensor. Typically, α is close to 1 to give more weight to the gyroscope data, as it is less affected by noise in short-term changes, while accelerometer data is used for long-term stability correction.

D. Hardware Setup

The prototype, designed using SolidWorks, employs two servo motors for 2-axis control movement. It incorporates an MPU6050 sensor, an Arduino Nano, a TP4056 charging module, and an 18650 battery for power.

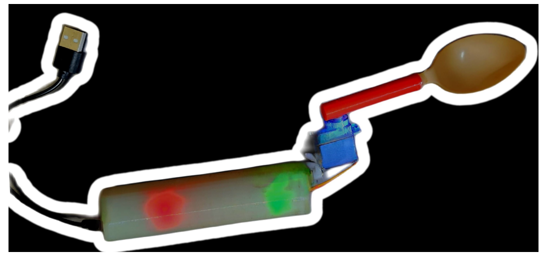

Fig. 3. Hardware implementation of the system

In assembling the prototype, acrylic was chosen for the housing and support due to its availability and affordability. Servo motor supports were attached to the housing using screws, repeated for the two servo motors utilized in the project.

To ensure wire organization, holes were created beside the housing for servo wires to enter, connecting to pins on the Arduino Nano. Details regarding servo motor connections will be provided later. Powering the project is facilitated by an 18650 battery positioned within the housing.

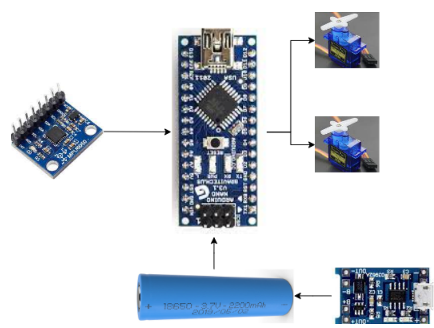

Fig. 4. Circuit Diagram of the System

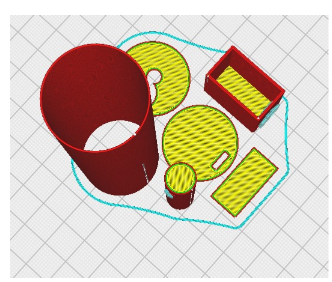

Fig. 5. 3D Model Of the System

The servo motor connections involve linking the signal wires of the servo motors to pins 8 and 9 on the Arduino Nano, while ensuring appropriate power and ground connections to the Arduino Nano or an external power supply.

Concurrently, for the MPU6050 sensor, the SDA (Serial Data) pin is connected to pin A4, and the SCL (Serial Clock) pin is connected to pin A5 on the Arduino Nano. Additionally, the VCC (Power) pin of the MPU6050 sensor is linked to the 5V pin on the Arduino Nano or an external power source, and the GND (Ground) pin is connected to the ground (GND) pin on the Arduino Nano or a shared ground within the system. These connections establish the communication and power supply necessary for the proper functioning of the servo motors and MPU6050 sensor within the prototype

III. Working of the System with Generative AI

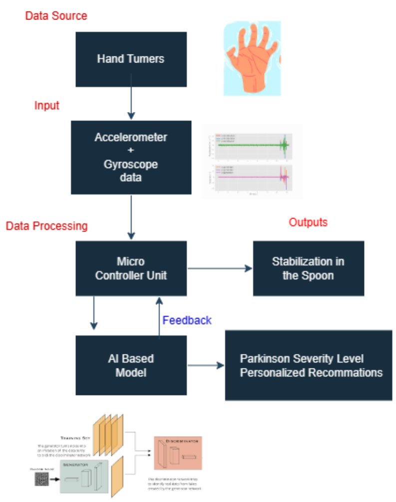

Fig. 6. System Outline with Machine Learning Algorithms

The basic functionality of the system was elaborated under section III. It was noted, during the development process, that the positioning of the spoon can be significantly improved with the use of Artificial Intelligence. Hence, the following approach was followed.

Initially, tremor data was collected from two Parkinson's patients—one with a mild case of the disease and the other with a severe case. Both patients were above 60 years old. The collected data consisted of accelerometer and gyroscope data. Using that data, a model was trained to detect the severity level of the patient holding the device. Once the model was trained, two approaches were available. First, the data read from the microcontroller was to be sent to the model and the response be sent via IoT. Since rapid response is a requirement of the device, that approach was discarded. The second approach was to deploy the model on the microcontroller itself. In this case, the trained model was converted to one that can be run on an ESP32 with the use of TensorFlow Lite. A PID controller was then implemented to stabilize the movement of the spoon. The values for the PID controller constant were chosen depending on the patient's severity level recognized by the model. However, this approach was proven to be erroneous as well. Particularly, the model had not been trained well due to not having a large enough dataset.

The machine learning models SVM (Support Vector Machine), SVC (Support Vector Classifier), and CNN (Convolutional Neural Network) were developed and trained for Parkinson's stage classification using the Python programming language. However, significantly accurate results could not be achieved due to the limited availability of data to overcome the issue of data availability, synthetic data is generated using CTGAN and evaluated using the TableEvaluator, but the expected output is not significantly developed.

The following approach was finally adopted. While observing the datasets from the patients, the following pattern was observed: When the tremor levels are more severe, the sign changes in accelerometer values are more frequent. Conversely, when the severity level decreases, sign changes become less frequent. Since accurate output couldn't be obtained using the previously explained machine learning model due to a lack of data, we chose to focus on the rate of sign changes, which resulted in successful outcomes. To achieve this goal, the code was adapted to allow the microcontroller to handle the task itself. Following this adjustment, improvements in stabilizing the spoon based on changes in severity level could be observed.

TABLE I
PID values corresponding to different operating modes

Operating Mode	Axis	Parkinson Stage	Kp	Ki	Kd
2*Basic Operation Mode	X	No classification method	1.05	0	0
	Y	No classification method	1.1	0	0
4*With Integrating ML	X	Low	1	0	0
		High	1.1	0	0
	Y	Low	1	0	0
		High	1.2	0	0
4*With Considering Accel. Change	X	Low	1.02	0	0
		High	1.15	0	0
	Y	Low	1	0	0
		High	1.2	0	0

The following figure represents accelerator and gyroscope data of severe Parkinson's patients.

TABLE II
Accelerometer and gyroscope values of severe Parkinson's patient

Time	AccX	AccY	AccZ	GyroX	GyroY	GyroZ
0.74327831	5860	2764	19852	-1216	12444	3929
0.743297836	1988	-4244	21744	-1200	6995	6911
0.743298924	-332	-4840	13376	-1232	1203	127
0.743300556	-3236	-9612	7960	-1200	-412	2135
0.743301632	488	-3364	14576	-1200	-514	-1605
0.743303264	488	-4112	13840	-1200	-641	-1064
0.743304352	-1232	-7508	11388	-1232	499	685
0.743305972	-1912	-7060	15476	-1232	-1063	495
0.74330706	-9248	-16740	3976	-1200	409	-8034
0.743308692	-12080	-19240	5736	-1216	-1432	-1747
0.743310313	-7992	-12492	5884	-1216	-114	3208
0.7433114	-2496	-5284	15560	-1216	-656	5211
0.743313032	3864	2276	15660	-1216	-785	6188
0.743314109	7724	10048	22620	-1248	-302	4522
0.743315741	10492	16180	24644	-1216	-804	9362
0.743316829	3072	8756	15704	-1248	1195	11442
0.743318449	2708	2264	13136	-1216	845	6386
0.743319537	2108	1612	12380	-1216	-1295	5660
0.743321169	-6684	-10016	12360	-1248	-966	2604
0.743322245	-7904	-11748	16132	-1232	-916	-1113

The accelerations and gyroscope readings obtained by the sensor are continuously stored in the Excel file. From this data, more synthetic data is generated .The synthetic data generation process involves utilizing the Conditional Tabular GAN

TABLE III
SYNTHETICALLY GENERATED ACCELEROMETER AND GYROSCOPE VALUES WITH STATUS

AccX	AccY	AccZ	GyroX	GyroY	GyroZ	Status
-2784	7968	16656	-1008	330	-570	high
-752	7132	13968	-960	2190	124	low
1328	8716	15740	-1056	-2455	-2136	high
-3412	-796	6260	-1216	10974	-4703	high
-4092	-404	17900	-1216	-2942	3292	high
-3628	8636	16812	-976	-575	-285	mid
-3556	6956	-13656	-1008	606	968	high
-1724	176	16296	-1216	1069	448	high
-1092	8900	19016	-1024	1120	763	low
1388	12492	-44	-1024	495	-1179	low
-644	2380	5228	-960	-5984	395	high
1092	-10016	17096	-1008	105	753	high
11936	7652	6724	-1024	378	-691	mid
-1440	6672	17924	-1024	-979	536	mid
-196	5548	14148	-1024	480	8244	high
-928	7228	17620	-960	-516	-709	high
-1184	8700	17240	-992	641	693	high

(CTGAN) model to generate data that closely resembles the original dataset, which comprises accelerometer and gyroscope values along with Parkinson's stage labels. CTGAN builds depend on a generative adversarial network (GAN) framework, where a generator network learns to generate samples that are indistinguishable from the real data. In contrast, a discriminator network learns to distinguish between real and synthetic samples. During training, the generator aims to minimize the difference between the distributions of the synthetic and real data, guided by feedback from the discriminator. This adversarial training process continues iteratively until the generator produces synthetic samples that closely match the statistical properties and distributions of the original dataset. Following training, the CTGAN model generates synthetic samples by sampling from the learned generator network. These generated samples are then evaluated through visual inspection, statistical analysis, and comparison with the original dataset to ensure they capture the essential characteristics and distributions of the real data. Additionally, the original and synthetic datasets undergo preprocessing steps, like data cleaning, scaling, and encoding of categorical variables, to prepare them for input into the Parkinson's stage prediction algorithm.

The total operating time of the spoon was detected using a generative AI-trained model. At the end of the day, a report was generated, which included the starting and ending operating times, as well as the total operating time of the spoon.

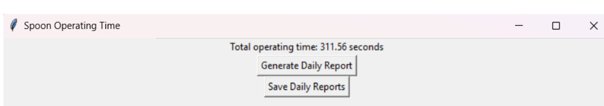

Fig. 7. Graphical user interface window displaying the usage time of a spoon

IV. RESULTS

According to sections II and III, the dynamic spoon is positioned by countering movements along the X and Y axes. Now, it is necessary to estimate the stability level. For this purpose, another MPU6050 sensor is placed on the spoon and connected to a separate Uno board. Subsequently, the output is plotted when the spoon experiences tremors. Simultaneously, the serial plot from the Nano board of the spoon is obtained. The two plots are then compared to evaluate their respective characteristics and performance. The following figure shows the testing setup.

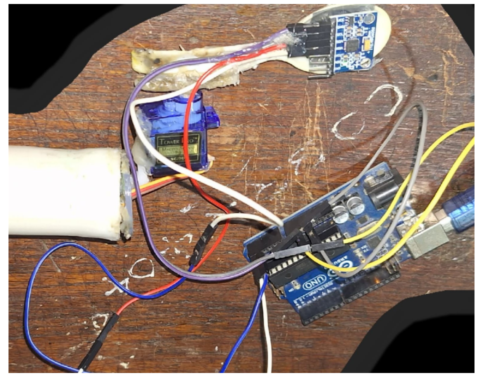

Fig. 8. Testing Setup

Figure 11 showcases the results without the ML model. The upper half of the Figure shows the graph of data from the sensor on the spoon, while the lower graph illustrates the tremors experienced by the spoon.

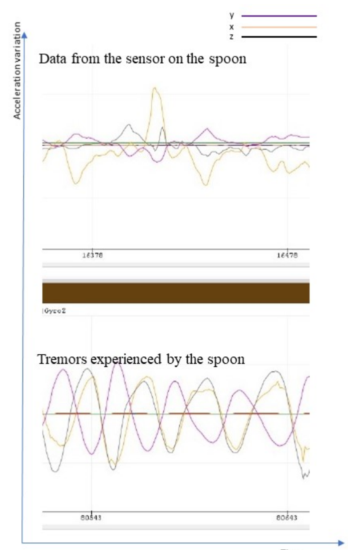

Fig. 9. Results Without ML model

As a solution to the case shown in Figure 9, a Machine Learning Model was implemented. However, the results did not show significant improvement as sufficient data was not available to properly train the model. Additionally, some inaccuracies were observed in the data as well. Although there was a slight improvement in the results, it was minimal. Figure 10 displays results obtained with the ML model.

Then, another method called direction changes was approached. In this method, rapid changes in hand acceleration direction occur during high tremors. By analyzing the acceleration direction changes, we were able to predict the stages and provide feedback to the system. Figure 11 graph illustrates the results of the direction changes method.

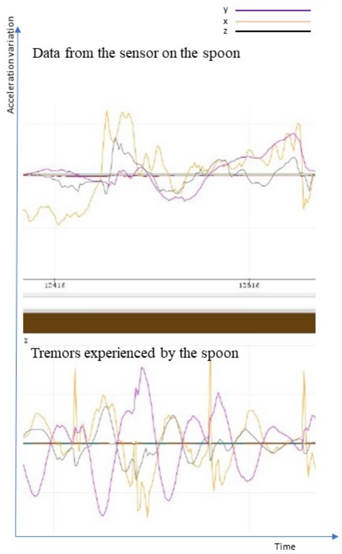

Fig. 10. Results With ML model

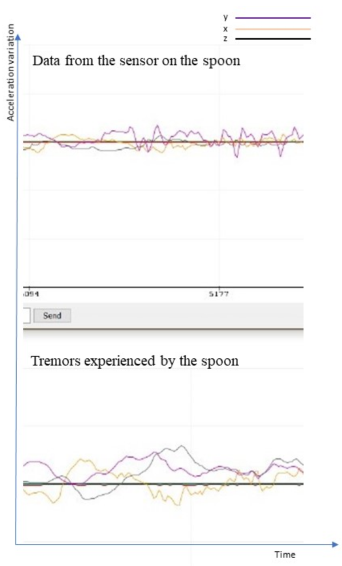

Fig. 11. Results with Direction change method

Even if the Direction Change method seems to be more accurate, the ML model may have given better results if it were well-trained with enough data.

Furthermore, a generative AI method is utilized to detect the stages of Parkinson's patients. Since data collected from patients were insufficient, synthetic data were generated. The collected data were categorized into low, mid, and high tremors, which were then fed into the machine learning system. Now, when the spoon is in use, the machine learning model receives sensor data and analyzes it over a certain time period to determine the stage as low, mid, or high. This approach can be further developed for stage prediction and monitoring the progress of taking medicine.

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