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A Low-Cost and Energy-Efficient Platform for Unsupervised Parkinson's Disease Assessment

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***Abstract*—Parkinson's Disease is a progressive neurological disease that affects roughly 6.2 million people worldwide. Current methods to control this disease via medication involve frequent and lengthy exams for hospitalized patients. Due to the inefficiency of traditional treatment monitoring, many professionals are currently pushing for in-home Parkinson's Disease examinations to lower costs while improving symptom response. In this paper, we propose a low-cost and energy-efficient hybrid system that monitors a patient's daily actions to quantify hand and finger tremors based on relevant Unified Parkinson's Disease Rating Scale (UPDRS) tests. We then evaluate its characteristics with regards to energy efficiency and medical accuracy. Finally, we compare the system with existing solutions to highlight its salient features.**

***Index Terms*—Tremor, Treatment Monitoring, Hybrid Device, Surface Electromyography, Internet of Things, Cyber-Physical System**

I. Introduction

Parkinson's Disease (PD) is a progressive neurological disease that affects 6.2 million people around the world [1]. Many advanced PD patients suffer from severe motor symptoms including arm and hand tremors, which increases the difficulty of performing daily tasks. Additionally, PD patients can suffer from other non-motor symptoms, varying from depression to sleep disorders [2].

Currently, Parkinsonian tremors can be effectively controlled through oral-medical therapies such as Levodopa, or invasive surgeries such as Deep Brain Stimulation (DBS) [3]. Although these treatments work, they are costly (approximately $\$22,800$ per patient [4]), highly patient selective, and can impose high risks [2], [3]. Furthermore, as the disease progresses, both treatments need adjustment according to the patient's symptoms to optimize their performance [5]. Therefore, it is important to continuously monitor a patient's symptoms for better treatment results.

Clinically, the severity of Parkinson's disease is measured using the Unified Parkinson's Disease Rating Scale (UPDRS), which medical professionals use to subjectively evaluate the patient's symptoms. The measurement of severity for PD is critical for understanding how to apply treatment. The professional community recognizes this importance and they are pushing for the automation of the UPDRS for more unbiased results [6].

The current state of the art in healthcare is built upon a feedback loop, which slowly responds to the advance of Parkinsonian symptoms. We aim to reduce the latency and improve the resolution of this feedback loop by improving the resolution to promote the timeliness of professional response. Our goal is to improve the measurement of PD through the use of home monitoring methods to reduce the need for extra doctor trips but providing the doctors with sufficient data to adjust medication.

In this paper, we propose a low-cost and energy-efficient platform capable of monitoring a patient's daily actions to quantify Parkinsonian tremors based on relevant UPDRS tests. Our design is primarily focused on operation in a home environment, where a patient has the freedom to act as they please.

The proposed platform utilizes a glove and a server. The glove houses a low-power microcontroller and sensors to continuously monitor a patient's Parkinsonian tremors at a frequency of 100 Hz. The glove transmits this data to a server, which processes the data using digital filters such as a low-pass filter and a Hampel filter. These filters generate additional features such as posture and movement.

It was important to us to build a platform that is accessible for the community, and so our testing focused on validation with respect to sampling performance and sampling accuracy. We found the measurement of our low-cost inertial measurement units to be similar to that of the expensive industrial sensor, but with a larger variance. The tested lifetime of the glove is approximately 15.16 hours when in constant use, which is considered sufficient for continuous monitoring. Our filters have been tested to demonstrate the capability to process regularly sized data sets quickly. Finally, the glove is run through an end-to-end sequence, demonstrating that the platform can collect data and produce a score estimate for the medical professionals.

This paper is organized as follows. In section II, we review our platform design. In sections III and IV we discuss the implementation of our glove and pipeline respectively. In section V and VI, we present our test results, compare them to existing systems, and discuss future work on the system.

II. System Overview

The Unsupervised Parkinson's Disease Assessment (UPDA) system uses a client-server architecture model and a pipeline architecture to model the behaviors of the glove and server, respectively. Figure 1 demonstrates that after the server has

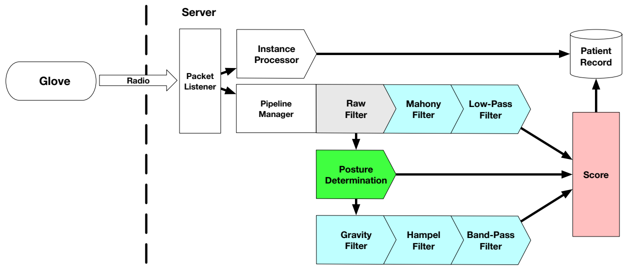

Fig. 1. Software architecture of system. The glove transmits patient data to the server over radio. The server then gathers and filters the data to produce UPDRS scores.

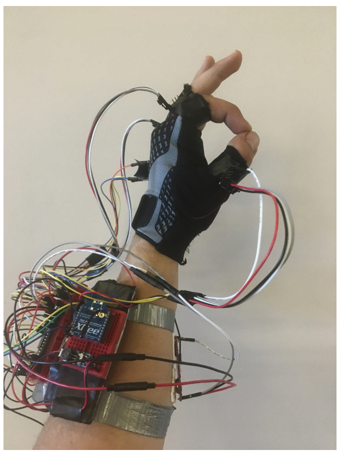

Fig. 2. Current prototype of the UPDA glove.

received the raw data from the glove, the server passes it through a series of filters in the signal processing subsystem. Each filter outputs new features, which are used to determine the UPDRS scores of a patient's Parkinsonian symptoms.

A. Glove

This section presents the design of the glove portion of the UPDA, which continuously monitors the occurrence of Parkinsonian symptoms during daily activities. To prevent major interference with user mobility during sampling, we picked a glove design for the wearable. The UPDA system focuses on data collection to evaluate finger and arm-based UPDRS tests. These tests require the detection of several actions including the movement of individual fingers and position of the entire hand.

Sensors are mounted onto the glove, ideally monitoring a user's precise actions without interfering with the patient's intentional movement. On the glove, four inertial measurement units (IMUs) are placed on the proximal phalanges of thumb, index finger, ring finger, and dorsum the of palm. Separated from the glove is an additional sensor for surface electromyography (sEMG), which is placed on the patient's forearm to measure muscular activity (Figure 2). The information from both the IMUs and the sEMG are used together to determine several of the postures and movements for automatic testing.

The system is designed using low-cost materials to improve accessibility for other professionals to rebuild the system. Additionally, we are interested in energy efficiency such that data can be measured for longer periods of time. More data improves the estimation of a patient's symptom severity.

B. Algorithms

The goal of the algorithms subsystem is to process all raw data collected from the glove to produce meaningful features, which helps provide diagnostics. For the scope of this project, we focus on six tests from the UPDRS, which cover finger and hand movement. To do so, we process acceleration, angular velocity, and surface electromyography (sEMG) readings from the glove to generate features that can help determine UPDRS scores.

The first two tests analyze finger taps and hand movement, requiring the system to generate features that can reflect a patient's desired movement without any tremors. We first implemented a low-pass filter to clear high-frequency noise caused by either the patient's tremor or by the glove itself. Additionally, we created a gravity filter, which separates the acceleration due to gravity from the raw acceleration.

The other four tests measure different types of tremors and their constancy. We use positional data and sEMG signals to determine at what times the patient exhibits postural tremor, kinetic tremor, and resting tremor. We designed a band-pass filter to isolate tremor signals to analyze amplitude and frequency. We use a Hampel filter to obtain clearer sEMG signals, removing outliers caused by poor contact between the sensors and the patient's skin.

III. Sensing and Communication

In this section we discuss the glove subsystem's design, individual components, and behaviors of the UPDA platform.

1) Sensors: The patient's hand position is monitored using four low-powered inertial measurement units (Invensense, MPU9250). An IMU contains an accelerometer, a gyroscope, and a magnetometer. These IMU features are synthesized to estimate orientation, which has proven useful for posture determination. To estimate orientation, we process the data through a Mahony filter [7]. Additionally, we measure the hand's muscular responses using a sEMG sensor to help validate its movement is caused by PD.

2) Wireless Radio: The radio communication between the glove and the server must be optimized for low-power usage, reliability, and range so that the system can cover an average household. Out of three popular wireless technologies: 802.15.4, 802.15.1 (Bluetooth), and 802.11 (WiFi), 802.15.4 [8] was the most suitable. Although Bluetooth can be low powered using Bluetooth Low Energy (BLE), the range and data rate are not sufficient to fit the needs of a home or hospital environment. A micro SD card is installed as a peripheral for reliable storage and to drive wireless connection. While transferring data, the processor will pull all of its samples from the SD card and send them over an XBee Series 1 (Digi International) using 802.15.4 based firmware.

TABLE I
WEARABLE GLOVE COST.

glove	Unit Cost	Quantity	Cost
Teensy 3.6	\$29	1	\$29
XBee S1	\$25	2	\$25
MPU 9250	\$15	4	\$60
Myoware EMG	\$38	1	\$38
		Total Cost:	~\$152

TABLE II
APPROXIMATE POWER CONSUMPTION OF UPDA GLOVE

Glove	Active Current Draw	Idle Current Draw
Teensy 3.6	79.13 mA	60 mA
XBee S1	50.0 mA	10 µA
MPU 9250	3.7 mA	8 µA
sEMG	14 mA	N/A

3) Embedded Controller: The microcontroller (MCU) coordinates all the other hardware elements on the wearable. Specifically, the glove uses an ARM Cortex-M4 MCU (Kinetis, MK66FX1M0VMD18), which uses a RISC-based architecture with a normal clock rate at around 180MHz. Using interrupt-based timers, the MCU is capable of sampling data in real-time reliably while maintaining a low power profile. Any major computations are passed off to the server, allowing the glove to focus mainly on sampling and power consumption.

4) Behavior: Our interrupt-based system is not able to sample data and send it immediately over the radio as a result of our decision to use a single-threaded microcontroller. Therefore to guarantee time, our glove has separate sampling and transfer states. During the sampling state, the MCU collects data from each sensor in a round-robin style at 100 Hz. Strict timing is guaranteed through an interrupt-based routine to perform sampling. The main thread then moves each sample from the buffer on to permanent storage on the micro SD for transmission. As the glove state transfers data, it pulls all sampling information from permanent storage for server transmission.

A. Cost

Cost is a key factor to make this platform accessible. In addition to providing low-powered sensory data and computing, the glove is chosen based on cost. Table I shows the cost of the main hardware for the wearable system. Given the low cost of the system and the relative ease at which a server could be purchased, the barrier to entry to reproduce this glove can be lowered.

B. Power Consumption

The system relies mainly on its hardware capability to continuously sample for sufficient periods of time such that UPDRS scores can be accurately estimated. Table II shows the approximate active and idle current draws for each sensor on the glove.

In addition to using low-power hardware, we can further extend the battery life of the glove by reducing the power usage of unused hardware. For instance, during the sampling state, the radio is using low-power. Inversely during the data transfer state, the IMUs are put into sleep mode. When the glove is in the transfer state and it detects that there is no more information to transfer, the MCU powers down the radio, the sensors, and itself to minimize energy consumption. It is essential to save as much energy as possible to ensure that most energy is spent when monitoring a patient.

Equation 1 gives the general formula for estimating the overall lifetime of the glove [9]. Equation 2 estimates a fifteen hour lifetime for the glove assuming a battery capacity of 2500 mAh and all hardware elements are constantly on. To extend the lifetime, we can employ power consumption strategies, which turn off different elements of the glove when they are not in use. Equation 3 estimates the battery life of the glove where each hardware element is idle, which provides a good upper limit to the performance of the glove. While testing the lifetime based on normal usage of the glove, we can estimate that the actual lifetime of the glove will fall somewhere between the hypothetical minimum and maximum calculations.

$$\frac{\textit{BatteryCapacity (mAh)}}{I_{ARM-M4} + I_{XBee} + (4 \times I_{IMU}) + I_{EMG}} \tag{1}$$

$$\frac{2500mAh}{79.13\text{mA} + 50\text{mA} + 14.8\text{mA} + 14\text{mA}} = 15.738\text{h} \tag{2}$$

$$\frac{2500mAh}{60\text{mA} + 0.010\text{mA} + 0.032\text{mA} + 14\text{mA}} = 33.76\text{h} \tag{3}$$

IV. DATA PROCESSING

In this section, we discuss the implementation of different filters, which produce key features to perform UPDRS scoring. We designed four different filters to apply to different raw signals collected from our sensors. We used a low-pass filter to prepare training data for machine learning, a band-pass filter to identify tremor, a gravity filter to remove the effect of gravity on acceleration, and a Hampel filter to eliminate spikes within sEMG signal. Finally, we use machine learning to perform posture determination using logistic regression.

A. Tremor Model

We had limited access to Parkinson's Disease patients, so we created a tremor model from the intentionally shaking hands of healthy subjects. We first validated the tremor data before using our glove and training our pattern recognition model. The frequency of a typical Parkinsonian rest tremor is above 4 Hz and can reach 9 Hz [10] and the range of acceleration is under 10 $\frac{m}{\sec^2}$ [11]. We applied a Fast Fourier Transform (FFT) on measured data to analyze our tremor model to determine whether our modeling is sufficiently accurate for further analysis.

Our tremor model has a peak magnitude of 6.8 Hz as shown in Figure 3, which falls into the range of PD tremor.

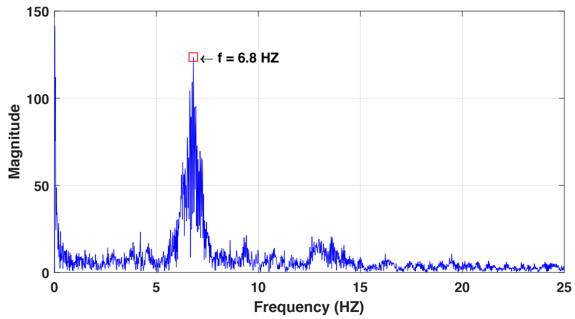

Fig. 3. We performed FFT analysis on our tremor model and obtained a peak magnitude at 6.8 Hz.

TABLE III
FILTER PARAMETERS

Filter	Low-pass Filter	Band-pass Filter
Filter Type	FIR	FIR
Order Mode	Minimum	Minimum
Passband Frequency	0-3 Hz	3-7 Hz
Stopband Frequency	3-4 Hz	2-3 Hz; 7-8 Hz
Passpand Ripple	0.1 dB	0.1 dB
Stopband Attenuation	80 dB	80 dB

Parkinsonian tremors also produce low accelerations, which allow for the measurement of tremors using accelerometers rated with a range of 16g. Unfortunately, we did not find any clear second or higher order harmonics, which are commonly shown in PD tremors [10]. This is expected because it is difficult to mimic the harmonics on patients without PD. We decided to continue using our tremor model for further analysis since the accuracy is sufficient for the scope of this project.

B. Filter Design

We designed two signal filters to extract the desired signal from the glove's raw data. A low-pass filter was designed to isolate the patient's intentional actions. A typical Parkinsonian tremor is above 4 Hz [10]. Therefore we set the cutoff frequency to be 3 Hz, and the stopband frequency to be 3 Hz to 4 Hz. We choose the finite impulse response (FIR) instead of the infinite impulse response (IIR) response filter for better performance on finite samples because we perform data analysis after data collection. A band-pass filter was designed to isolate tremor signal from raw data. We chose 3-7 Hz as our passband to include all tremor information from our tremor model. The parameters of our preliminary filter designs are listed in Table III.

We use Filter Builder in MATLAB to build these two filters based on the parameters listed in table III, which returns lists of filter parameters. We then perform convolution between the raw signal and the filter coefficient array to obtain filtered signal using Equation 4.

$$(Signal * Filter)(t) = \int_0^\infty Signal(\tau) \cdot Filter(t-\tau) d\tau \quad (4)$$

C. Gravity Filter

Given the limitation of the low-cost IMUs we are using, it became necessary to remove gravitational acceleration from the measured acceleration to extract the acceleration caused by patient movements. First, we use a Mahony filter [7] to convert acceleration, angular velocity, and orientation with respect to the earth's magnetic field into orientation estimated represented in quaternion coordinates. We then apply these calculated coordinates to the rotational matrix shown in Equation 5, to convert the gravitational acceleration vector into the IMUs' frame of reference.

$$g(x) = 2 \cdot (i \cdot k + j \cdot r) \cdot G \quad (5a)$$
$$g(y) = 2 \cdot (j \cdot k - i \cdot r) \cdot G \quad (5b)$$
$$g(z) = (r^2 - i^2 - j^2 + k^2) \cdot G \quad (5c)$$

where

$$G = -9.81 m/(s^2) \quad (5d)$$
$$quaternion = [r, i, j, k] \quad (5e)$$

Combining the measured acceleration and gravity acceleration, we obtain the actual acceleration as follows:

$$a_{true}(x, y, z) = a_{measured}(x, y, z) + g(x, y, z) \quad (6)$$

D. Hampel Filter

We used a Hampel filter [12] to remove the random spikes in sEMG recordings likely produced from poor contact between the patient's skin and the sEMG electrodes. The algorithm is based on the sliding window philosophy, where the moving window size is chosen to be 17. This means we replaced the outliers of the median of the neighboring eight data points to the left and to the right respectively (Equation 7).

$$m_k = \text{median}\{x_{k-8}, \ldots, x_k, \ldots, x_{k+8}\} \quad (7)$$

E. Posture Determination

We use logistic regression to classify different, specific hand positions that are useful for UPDRS evaluation. We focus on the finger taps and hand movement tests from the UPDRS, which requires us to recognize four actions including finger tapping, a fist making, and any interruptions while performing either.

First, we gathered relevant data for training a model to accurately predict hand movements. We obtained data from three team members, who each performed several variations of the choreographed movements. For each variation, we gathered 10 samples and used that data to train our models. This training process is performed by initializing random weights, calculating the gradient, and following its descent towards the minimized cost as shown in Figure 4.

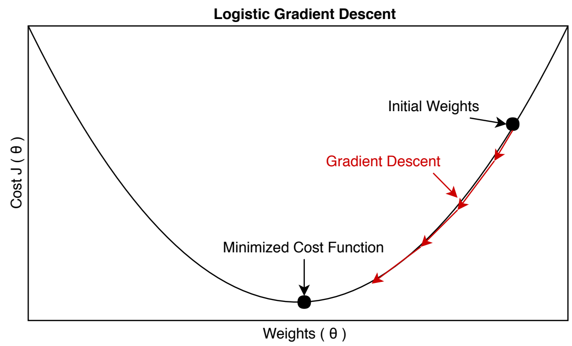

Fig. 4. This is a generalized graph to help conceptualize the way gradient descent works. We begin by initializing random weights and then following the gradient by updating the weights until we have a minimized cost function

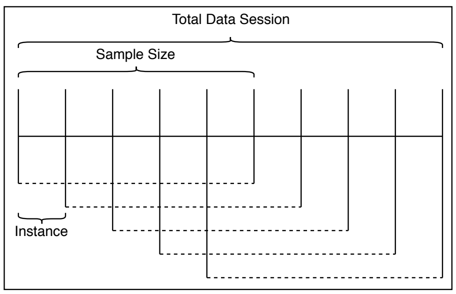

Fig. 5. We gathered 480 data samples and generated 57,480 unique data samples.

Machine learning models, however, only function as intended when enough quality data is available to train on. To maximize the quantity of our data, we have developed a form of data manipulation that takes a single sample of data and shifts by 1 as shown in Figure 5. This process results in a larger and unique data set containing more samples. We chose four frequencies in which a sample can occur, 0.33Hz, 1Hz, 2Hz, and 3Hz, which correspond to 300, 100, 50, and 33 instances per sample, respectively. We collected 120 samples for actions in each frequency totaling 480 samples. With this shifting method, we generate 57,480 samples in total for training our 16 models (Figure 5).

Finally, we tested its prediction accuracy by having it process a similar dataset and compare its predictions with expected values. With these results, we sought to minimize the error rate of our model. To reduce errors from the model over-fitting the data, we used cross-validation, feature removal, and regularization.

V. Results and Discussions

This section presents the results validating the glove and filters. With regards to verification of the glove as a platform for consistent sampling, we are testing energy efficiency and accuracy. We are testing filter functionality and filter processing performance.

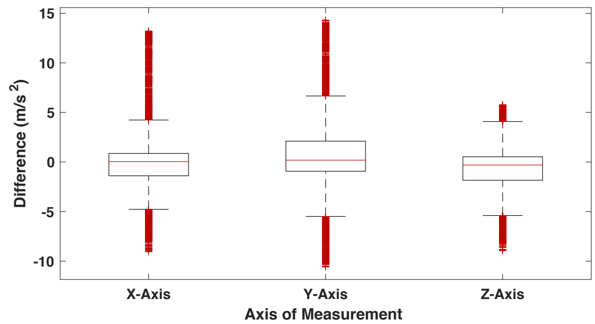

Fig. 6. Comparison of accelerations measured between two IMUs: the MPU9650 and the Physilog5.

A. Energy Efficiency

The energy efficiency of the glove determines for how long a patient's wearable glove can collect and transfer data for UPDRS scoring. The goal was to test the actual lifetime of the glove before applying power consumption behaviors. The glove was powered on the test bench with all hardware actively working, to determine how close the actual battery life was to the calculated battery life according to Equation 2. The test results are close to that of the calculation, showing that the glove lasted approximately 15.16 hours during constant normal usage before losing its capability to power any one component.

B. Measuring Accuracy

The quality of the low-cost inertial measurement units has been evaluated through a side-by-side comparison with the Physilog5 sensor [13], which has been recommended for medical sensing and evaluation. We compared the quality of the MPU9250 to the quality of the Physilog5 sensor to justify its potential as a lower cost medical platform. The sensors are compared by placing the Physilog5 on top of the glove's IMU located on the dorsum of the palm. Both gloves were oriented such that the axes are similar. The tester then performs five minutes worth of fast and slow movements to evaluate sampling ability. Both data sets are then subtracted from each other to find the difference. Figure 6, presents box and whiskers plots for each axis of acceleration compared. The medians of each plot are approximately zero, but all contain large variances and a large range of outliers. This is expected because of the large difference in cost and advertised quality between the two sensors. While the Physilog5 sensor measures far more accurately, we can potentially filter out the outliers from the MPU9250 to make it more stable for medical monitoring.

C. Data Processing

Several different filters are presented in the previous sections for which we want to test both the efficiency and the performance.

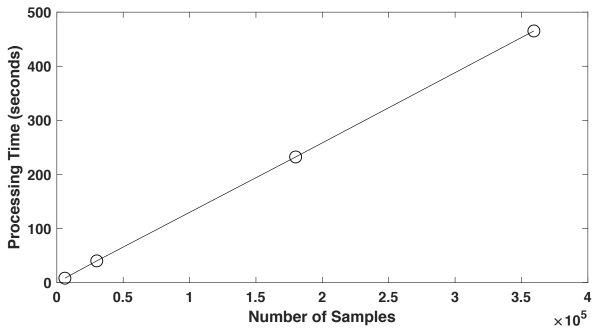

Fig. 7. Processing time of raw data through pipeline filters

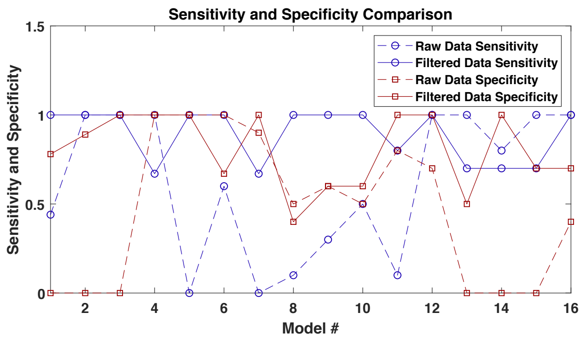

Fig. 8. We compared the performance of using raw data versus filtered data for position determination. The filtered data described in the solid lines performs better on average than the raw data in the dashed lines.

1) *Filter Efficiency:* The efficiency of the filters is proportional to the time spent processing the data. We tested different order modes, stopband frequencies, passband ripples, and stopband attenuation to obtain a suitable filter design. Additionally, we tested each filter with a one-hour dataset measuring random movement. The collected results confirm that our initial design worked best in terms of speed and accuracy.

On MatLab, filtration of an hour of data costs 0.2 seconds, implying the filters are sufficiently fast for daily real-time implementation.

Additionally, the entire pipeline performance was tested. Figure 7 shows the approximate linear increase of the pipeline's processing time proportionally increases with the linear increase of the raw data. The proportional linear increase is promising with regards to system scalability for future platform development.

2) *Filter Performance:* The performance of the low-pass filter is determined by its contribution towards improving position determination. We used both raw data and filtered data to train two machine learning models and compare the accuracy of both. We compared the sensitivity and the specificity of all sixteen models and plotted the results in Figure 8. The low-pass filter can improve both the sensitivity and specificity of the machine learning algorithm by keeping both rates above 0.4.

The performance of the gravity filter is tested by placing the

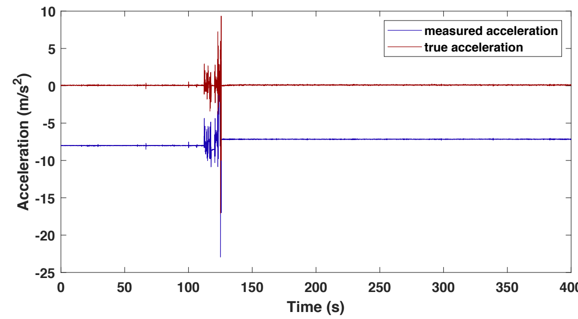

Fig. 9. Comparison of the measured acceleration with true acceleration generated by gravity filter. The gravity filter generates approximately zero when the sensor is stationary.

sensors on a stable surface and rotating the sensors without moving their center of gravity. After the application of the gravity filter, the accumulated acceleration is estimated to be close to zero. We used four-hundred seconds of raw data for testing, with the result plotted in Figure 9. Our results show we can correctly rectify raw data. We adjusted the sensor positions between times one-hundred seconds to one-hundred fifty seconds, and the gravity filter performed well under different sensor positions.

VI. Related Work

The volatility and progression of PD symptoms have inspired the healthcare community to introduce home monitoring to PD patients. One recent review emphasizes the significance of wearable technology and its potential impacts for controlling tremors [14]. In this report, tremors have also been cited as one of the most disrupting symptoms in one's daily life. Through the accessibility of wearable technologies, there lies the potential to improve our response to Parkinsonian symptom fluctuation.

Many researchers and teams are aiming to improve the UPDRS scoring process [5], [15]–[20]. All of these researchers utilize the same types of equipment, including sEMGs and inertial measurement units to collect data. However, each team utilizes this information differently to develop new insight for the UPDRS scoring automation process.

Several research teams sought to design systems focused on enabling patients to interact with healthcare professionals from their homes [17], [18]. These methods demonstrate successful web service designs. These designs reduce the cost of travel and continue to provide professionals with sufficient data to accurately evaluate the patient's condition. Furthermore, these methods show how patients can reliably perform the necessary actions at home in order to perform evaluations [21]. These systems, while they provide more quantitative data, still require a doctor to objectively make decisions, which may still affect the outcome of the treatment.

Many studies focused on creating automated UPDRS scoring systems [5], [6], [15], [16], [19]–[21]. These automated UPDRS scoring systems also are subdivided into systems that rely on guided human movement such as a UPDRS test example [21], or systems that monitor unguided movement [5], [6], [15], [16], [19], [20]. Several of the automatic scoring systems attempt to utilize machine learning to classify the different scoring metrics [5], [16]. Unfortunately, both teams agree that machine learning, while promising, does not meet a high enough accuracy to perform as a suitable scoring method [5], [16]. Other teams integrated numerical methods and different classifiers to explore the kinematic features correlated to specific UPDRS scores. One team created a promising method for automatic UPDRS scoring system for gait symptoms, which relies on the linear relationship between several kinematic features and the actual UPDRS scores [20]. Another team has designed a methodology that produces highly accurate estimates of tremors for UPDRS using an inertial measurement unit on a wristband [15].

There are many different strategies for performing automated UPDRS scoring, but none are embodied inaccessible products in the market. Therefore our aim is to provide a platform that can support research for truly automated UPDRS scoring, starting with hand, finger, and tremor tests. To provide sufficient, data we have been designing a glove with the goal that it can sample for extended periods of time. Our server architecture incorporates filters to extract important features for users, and modularity such that other developers can add, update or create a new filter. Machine learning classifies the user's different positions and includes them for the scoring algorithm.

VII. Discussion

There are limitations that we seek to address in the future. For instance, the current model cannot sample and transmit simultaneously in real-time. The current glove additionally contains a set of minor hardware and software bugs that reduce the battery lifetime, which we intend to fix in the next model. While the prototype was functional for basic testing, it is far too large to be comfortable on a patients arm, and the hardware should be reduced to a more manageable size. On the server side, we plan to add the support for multiple gloves at once for better use in hospitals or for research. We are also interested in improving the server software to improve accessibility to health care professionals, who can review the evaluation and adjust medication appropriately.

With limited access to real PD patients, we were unable to design unique filters for each patient. Real patient data enables customizable filter parameters, such as cut-off frequency, to better prepare the signal for pathology analysis. We are also interested in designing different passbands for the band-pass filter to isolate postural, kinetic, and resting tremors for better understanding how these tremors change with disease progression. Finally, as the platform develops, we would like to test medical accuracy with a doctor's diagnosis and try to reach a higher accuracy than that of general professional diagnosis.

As we have implemented our machine learning models and tested its limits, we believe that our method is verifiable since the models are capable of determining the positional information for the UPDRS test. However, there are some shortcomings in our design. For instance, although we have managed to replicate tremors, our data is still lacking tremor data from actual patients. We redesigned our model to compensate for our lack of Parkinson's Disease patients, and make our best attempt to model tremor data [22]. After conducting a series of tests, we have determined that it performs on average above 50% accuracy. However, to better the model, we recognize the need for real patient data.

The results presented in this paper serve to state confidence that this system holds merit as a platform for automatic UPDRS scoring. The tests presented in this paper have been performed by the development team since the resources to perform testing on PD patients were unavailable. We intend to gather resources to undergo future patient testing and further the platform. Ultimately, we hope this platform can serve other researchers and health care professionals as a useful tool in the future.

VIII. Conclusion

In this paper, we presented the preliminary design and validation of a system that automatically scores portions of the UPDRS based on a patient's regular movements. To verify this system, we designed experiments to confirm its functionality by gathering raw data and producing features through filters. Our current version of the glove is capable of supplying researchers and patients with continuous symptom monitoring at useful resolutions. The system architecture offloads the heavier processing onto the server, enabling more powerful data processing than possible using just the glove. The server also creates options for future services; doctors with permissions could request patient data remotely for simplified treatment adjustment.

We intend to continue working on the system; improving its functionality for health care professionals in addition to improving scoring quality. We would also like to organize patient testing with a facility that is capable of gathering information from actual patients. Overall, this platform has demonstrated potential to found future development for wireless PD monitoring and we are excited to see to what lengths this system is used.

Acknowledgment

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