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DATA ANALYTICS FOR WEARABLE IOT-BASED TELEMEDICINE

BY

RASSOUL DIOUF

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENTS FOR THE DEGREE OF

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OF

RASSOUL DIOUF

APPROVED:

Thesis Committee:

Major Professor Kunal Mankodiya

Yan Sun

Mustafa Kulenovic

Susan D'Andrea

Nasser H. Zawia
DEAN OF THE GRADUATE SCHOOL

UNIVERSITY OF RHODE ISLAND
2019

ABSTRACT

Parkinson's disease (PD, Parkinson's) is a common neurodegenerative disease affecting over 10 million individuals worldwide. Its main marker is the loss of dopamine-producing neurons in the substantia nigra, an area of the midbrain. The root cause of PD is currently unknown. Besides, the disease is progressive, and the symptoms worsen as the ones affected grow older. Motor symptoms such as tremors, slowness of movement, and muscular rigidity, along with other non-motor ones, such as trouble with sleep, may occur. The current solutions for PD are medication and, in cases when the disease does not respond to it as much as one would like, a surgical procedure called Deep Brain Stimulation (DBS) as an alternative. Although they don't suppress or reverse the neurological damage, these solutions do help alleviate the symptoms. For proper dosage of medication and/or calibration of DBS, PD patients go through a screening process during which the progression of the disease is assessed. This process comes, unfortunately, with hurdles. These include the need for doctor visits for a person dealing with several symptoms, and the suboptimal screening frequency given the progressive nature of Parkinson's.

The rise of IoT and the field of Analytics has unlocked new and technology-inclusive means of managing healthcare. With the vast amounts of data spawning from countless sources, along with the advances in communication technologies, it might not come so much as a surprise that Data is at the center of many sectors today. From everyday

devices such as watches or smartphones, sensors have become increasingly common due to their smaller size over the years, as well as becoming less expensive. It naturally comes from this fact, then, that many opportunities to make improvements centered around these technological advancements are arising. One of those being in biomedical engineering, where the ubiquity of sensors has improved many facets of how we are able to understand the human body. Parkinson's Disease management is an area that could greatly benefit from it, and this section will present some possible solutions in the specific applications of PD monitoring and diagnosis. Using physiological sensors and remote-management architectures, can we improve the management of the disease?

This thesis was written based on a study in which we recruited 2 healthy participants, and 4 PD patients. Data from UPDRS-III movements was collected with electronic textiles (e-textiles), then processed using time, frequency, and time-frequency domain methods to obtain relevant features, as hallmarks of Parkinson's. These features were then used in MATLAB's Classification Learner to build a binary-classification model for each UPDRS task to distinguish between PD and non-PD. These models yielded accuracies ranging from 81.0% to 99.3%.

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CHAPTER 1

INTRODUCTION

Parkinson's Disease (PD) is one of the most prevalent neurodegenerative diseases, with over 10 million people affected worldwide, including 1 million in the US [Parkinson's Foundation]. And amongst those who are healthy, 60,000 are diagnosed with PD every year in America. Given the increased incidence of the disease with age [Marras et al.], coupled with a growing elderly population in the US (and the rest of the world), there is more than ever a need to find reliable and effective healthcare solutions to ensure that the health of current, as well as future patients is properly managed.

Parkinson's is a motor-system disorder that occurs as a result of the loss of dopamine-producing neurons in basal ganglia (i.e. the substantia nigra) [Cookson]. Dopamine being responsible for controlling movement, emotional responses, as well as the ability to feel pleasure and pain, PD patients find themselves suffering from various physical (and psychological) symptoms. Common symptoms of the disease include tremor, stiffness, and slowness of movement. PD is also known to be both chronic and progressive. That is, it not only persists over time, but its symptoms get worse. Rudimentary activities such as walking or talking become increasingly difficult as the disease progresses. And although no cure has yet to be identified for PD, there exists a variety of treatments that exist to alleviate symptoms, such as medicating the patient

with levodopa. In certain cases, however, when PD doesn't respond to medication, surgery may be appropriate. Specifically, a surgical procedure called Deep Brain Stimulation, or DBS, is used as an alternative to alleviate the symptoms. DBS is the insertion into the brain of electrodes connected to a pulse generator, to help reduce tremor and other symptoms. The therapy does require, importantly, careful programming and calibration to function properly. In that regard, neurologists perform a screening process called the Unified Parkinson's Disease Rating Scale (UPDRS). As its name suggests, UPDRS is universal scale of PD symptoms used to assess the disease's progression. The score resulting from the process ranges from 0 to 4, respectively corresponding to a clinical evaluation of normal, slight, mild, moderate, and severe inability to perform the task. The screening consists of four different parts. Parts I and II are the reporting by the patient of his/her daily experiences. Part III is a motor examination of the use of a standard set of movement exercises. Part IV deals with motor complications. Part III, which deals with movement exercises (UPDRS III), will be of interest for this project. UPDRS-III exercises include, but are not limited to, hand movements, postural stability, foot-tapping, and finger-tapping. Using the latter as an example, neurologists might observe how many taps the patient can perform in a set amount of time, which can essentially be interpreted as the frequency of taps.

[Parkinson's UK]

Research Innovation

Although very useful in optimizing DBS for each patient, the screening process is very time consuming and tedious, and can be expensive, as well. One very potent way of facilitating this process would be the adoption of telemedicine in the monitoring of PD patients. Telemedicine, simply put, is the inclusion of information technology and telecommunication in the provision of healthcare. It takes advantage of the advancements in the field of IoT to integrate health monitoring as part of an organized and efficient architecture and can help migrate many healthcare-related practices to non-clinical environments.

Figure 1 -Overview of IoT-based e-textiles solutions for Parkinson's Disease

The proposed architecture shown in this thesis [Fig. 1] will involve the use of electronic textiles (e-textiles) for data collection, and the use of smart devices, such as tablets, for analytics. The challenge of designing the e-textile, has already been achieved, and continues to be improved. Validating these wearable devices is crucial in their development, and the aim of this project will be to develop and implement data analytics solutions to investigate the effectiveness of the e-textiles in identifying markers of PD.

CHAPTER 2

BACKGROUND

1. Symptoms and pathophysiology

1.1 Symptoms of Parkinson's Disease

Parkinson's disease patients live with a variety of symptoms, especially at advanced stages. Symptoms of PD can be categorized into two types. Motor symptoms and non-motor symptoms.

The non-motor symptoms of Parkinson's disease [Fig. 2] will, in general, precede the motor symptoms, even by years in some cases. They may include depression, anosmia, or sleep problems [Cookson]. Because they are common to several other conditions, it is very difficult to reach the conclusion of PD diagnosis based solely on them. Motor symptoms, on the other hand, are the main indicators observed by medical professionals while diagnosing Parkinson's disease.

Figure 2 -Non-motor symptoms of PD [Qamar et al.]

One of the most common symptoms of Parkinson's is tremor. PD patients may suffer from different types of tremor. Mainly, affected individuals will display rest tremor of around 4-6 Hz. However, postural and action tremors are also common. Along with tremor, patients experience additional motor symptoms such as bradykinesia (generally characterized by slowness of movement), muscular rigidity, and postural imbalances. Figure 3 shows more examples of motor symptoms that a PD patient may experience. These symptoms may, however, appear in individuals who do not have PD. Specifically, these people might have what is referred to as secondary parkinsonism. Thus, for a patient to be diagnosed with PD, two conditions need to be met: bradykinesia and one of tremors and rigidity must be observed in the patient; additionally, potential causes of secondary parkinsonism need to be eliminated from contention. [Ahmed & Sweeney, Sveinbjornsdottir, Davie, De Lau]

Parkinson's Disease Symptoms

Figure 3 -Motor symptoms of PD [APDA]

1.2 Pathophysiology

Parkinson's disease symptoms occur as a result of the loss of dopamine-producing neurons in an area of the brain called the substantia nigra [Fig. 4], which itself is part of the basal ganglia. By the end of a patient's life, this part of the brain would lose about 50 to 70 percent of its neurons compared to those unaffected. The basal ganglia are a part of the brain that, as a highly organized network, is involved in not only movement control, but also in associative learning, working memory, to name a few. And dopamine plays a crucial role in those functions. That, in fact, explains the motor symptoms that PD patients display.

Parkinson's disease is a progressive neurodegenerative disease. This progressive nature of PD is believed to be related to the pathological accumulation of Lewy bodies and Lewy neurites, which consist of proteins and lipids. As the patient ages, the disease progresses, and symptoms tend to become worse. Although PD patients are prescribed medication, and some others go through DBS [Fig. 5], evidence seems to suggest that current solutions are not neuroprotective, thus do not slow down, let alone stop the progression of the disease. The root causes of PD are still unknown, and research in that field is ongoing. [Lang, Obeso, Davie, Cookson]

*Figure 4 -Illustration of decrease in dopamine production in the substantia nigra
[Harvard Health]*

1.3 Current Solutions

1.3.1 Treatment

There is currently no known cure for Parkinson's disease [Davie]. But there are, in the meantime, treatment options that help mitigate the symptoms. Medication, such as with levodopa or anticholinergics, is one solution.

Figure 5 -Deep Brain Stimulation [UC Davis Health]

Ideally, medication for Parkinson's would initiate a reversal process of the neuropathological damage caused by the disease, and lead to normally functioning substantia nigra again. Unfortunately, currently available medication does not serve that purpose. The most popular medication-based therapy for PD is levodopa, a drug aimed at directly supplying dopamine to the brain [Cookson]. Other downsides of using levodopa is the eventual decrease in the positive effects that the therapy has, due to adaptation [Thanvi & Lo]. This, of course, is an issue because the medication would need to be taken continually. And when medication becomes of little to no effect on PD, many opt for Deep Brain Stimulation.

DBS is a procedure in which high-frequency stimulating electrodes, connected to a pulse generator, are surgically placed in the brain to help reduce tremor and other motor

symptoms. The therapy does require, importantly, careful programming and calibration to function properly. In that regard, neurologists perform a screening process called the Unified PD Rating Scale (UPDRS).

1.3.2 Screening

For proper provision of these relief solutions, PD patients need to go through a screening process called the Unified Parkinson's Disease Rating Scale (UPDRS), which is a universal scale of PD symptoms used to assess the disease's progression. The score resulting from the process ranges from 0 to 4, respectively corresponding to a clinical evaluation of normal, slight, mild, moderate, and severe inability to perform the task. UPDRS screening has been provided with both scientific and clinical credibility, through several analyses. It is widely utilized and reliable [20].

The screening consists of four different parts [Fig. 6]. Parts I and II are the reporting by the patient of his/her daily experiences. This involves mentation, behavior, mood, and activities. Part III is a motor examination of the use of a standard set of movement exercises. Part IV deals with motor complications. This screening process come with a few hurtles, unfortunately. To better understand them, let's first investigate whom this disease affects the most. The next section will discuss the epidemiology of the disease.

UPDRS Assessment Protocol			
Observer	Part	Domain	Tasks
Patients & Caregivers	1	Behaviors	1-4
	2	Activities of daily life	5-17
Physicians	3	Motor exams	18-31
	4	Complications	32-42

Motor Exams	
18. Speech	25. Rapid altering hand movements
19. Facial expressions	26. Leg agility
20. Tremor at rest	27. Arising from chair
21. Postural tremor hands	28. Posture
22. Rigidity	29. Gait
23. Finger Taps	30. Postural stability
24. Hand movements	31. Body brady-/hypo- kinesia

Figure 6 -UPDRS screening protocol and list of motor exams conducted by neurologist in clinic

2. Epidemiology

In North America:

Parkinson's disease is one of the most common neurodegenerative diseases, being second only to Alzheimer's disease. Marras et al. (2018) have reported the prevalence of PD to be of approximately one million in the United States alone. And with an incidence rate of about 60,000 new diagnoses per year [Parkinson's Foundation], this number is projected to surpass 1.2 million by the year 2030. Worldwide, more than 10 million people suffer from the disease. Although the demographics of Parkinson's disease patients do vary with respect to geographical region, some trends seem to stay consistent across. And that is the fact that the incidence of PD increases with age.

In partnership with the Parkinson's Disease Foundation, Marras et al. have performed a meta-estimate of PD prevalence by age across North America, using data from the regions of California, Minnesota, and Hawaii, USA, as well as from Ontario, Canada. Disregarding the patients' gender, the study found the respective prevalence of Parkinson's, per 100,000, to be 114 for the ages of 45 to 54; 457 for ages between 55

and 64; 1,638 for ages 65 to 74; 4,296 between 75 to 84; and 6,291 for populations aged 85 and above. What stands out immediately is the sudden increase in PD prevalence past the age of 65 [Fig. 7].

Figure 7 -Parkinson's Disease prevalence meta-estimate for North America [Marras et al.]

Around the world:

Although there are certain differences in prevalence and incidence with respect to gender, ethnicity, and geographical location, this correlation between age and prevalence remains true. Abbas et al. (2018) have found that PD prevalence is, in general, lower in “Eastern” regions, such as Asia and the Middle East, than in “Western” regions, such as the Americas, Australia, and New Zealand. The same was true for the incidence of Parkinson’s. In Eastern countries, although there was a male predominance in PD prevalence, this disparity was found to be even more evident in Western countries, where males are 1.5 times more likely to be diagnosed with Parkinson’s disease. What did remain consistent, however, was that both in Eastern and Western regions, Parkinson’s prevalence increases with age. This reason, added to an increasing elderly population—given that the US population aged 65 and over is projected to grow to 81 million by 2050 [Passel & D’Vera], makes healthcare planning for elderly populations crucial in the coming years.

3. Problem tackled

When subjected to this screening process, PD patients first go through an initial calibration period during which the patient visits the doctor every 2 weeks. This phase may last for as long as necessary to make sure the calibration is correct. The second phase, which is the continual one, consist of visits that happen every 4 to 6 months. There, partly lies the problem. Although very useful in optimizing DBS and medication dosage for each patient, the screening process is very time consuming and tedious, plus

can be expensive. Besides, the frequency of visits might not be optimal, given the progressive nature of the disease. As shown in the previous section, there is a significant increase in the prevalence of PD for ages 65 years and above. Given their age and the several motor symptoms they suffer from, going through the screening process can involve lots of hurdles in the life of a PD patient. Part III, which deals with movement exercises (UPDRS III), will be the part tackled by this project. Solving this problem will come down to answering the question of whether the UPDRS-III screening process can be migrated to non-clinical environments. UPDRS-III exercises include, but are not limited to, hand movements, postural stability, foot-tapping, and finger-tapping. Using finger tapping as an example, neurologists might observe how many taps the patient can perform in a set amount of time, which can essentially be interpreted as the frequency of taps. The aim, then, is to capture that same information without needing the neurologist's assessment through observation. To do so, the use of e-textiles is proposed, the latter being simply textiles with electronics embedded in them [Fig. 10].

The e-textiles by themselves, however, do not solve the said problem. It needs to be in an architecture that enables the desired migration of the screening process. One very potent way of facilitating this would be the adoption of telemedicine in the monitoring of PD patients. Telemedicine, simply put, is the inclusion of information technology and telecommunication in the provision of healthcare. It takes advantage of the advancements in the field of IoT to integrate health monitoring as part of an organized and efficient architecture and can help migrate many healthcare-related practices to non-clinical environments. After an overview of what the Internet of Things is, and

what it consists of, we'll explain how an IoT architecture fits into our aim of migrating the screening process.

4. The Internet of Things

The Internet of Things (IoT) can be defined as a network of interconnected sensing and actuating devices that can share information [Gubbi et al.]. Architecturally, IoT consists mainly of three layers: the “Things” layer, which are local devices (sensors, actuators etc.), the “Edge” layer (smart devices), and the “Cloud” layer (the Internet) [Fig. 8]. Things will gather data (physiological, environmental data etc.), or even perform specific actions based on received information. The Edge is the layer between the Things and the Cloud, where processing and visualization can be done before anything is sent to the Cloud. The Cloud, then, is the layer of the IoT where data is stored and transferred between different IoT servers (data processing can also take place in the Cloud).

Figure 8 -Generic IoT architecture [Seeburn]

The proliferation of Data

Today's world is submerged in "Data". From one's step-count to one's location history, or even online-shopping habits, we are generating large amounts of data every day. This significant growth in the availability and use of data has resulted in, almost, a banalization of the term. Yet, although privacy and security might be of major concern—and this matter will have to be an entirely separate discussion, Data is the key to uncovering hidden insights, as well as answers to a multitude of questions that may not even have been asked yet. Companies and researchers in almost any sector, such as e-commerce, Media, and Healthcare (which is of interest in this project) [Fig. 9], use data

that they gather to come up with relevant information that is likely to influence their future directions. One of the most widely known ways data analytics impacts our everyday lives, is in the results from user-generated data in Internet video-streaming services. As users spend time on these services, countless amounts of data are generated over time. With analytics, unique signatures and trends in preferences can be identified for every individual. Likely, every single person's homepage on a web/mobile application such as YouTube will look different, given the variety of content that different people consume on the platform. Similarly, services like Netflix will suggest different movies and TV-shows to different people. In e-commerce, vendors have found in the use of analytics a completely new way to quantify the demand for every product, thanks to user-generated data. This data has also enabled the generation of targeted ads, which have completely revolutionized the way retailers advertise and sell their products. In Healthcare, the capturing and analysis of physiological data is quite common and has been for a while. Uses for sensors such as electromyograms (EMG), electrocardiograms (ECG/EKG), photoplethysmograms (PPG), to name a few, are very well studied and understood.

<i>Sectors</i>	<i>Video</i>	<i>Image</i>	<i>Audio</i>	<i>Text/Numeric</i>
Banking	Medium	Medium	Medium	High
Insurance	Low	Low	Low	High
Retail	Medium	Low	Low	High
Wholesale	Low	Low	Low	High
Utilities	Medium	Medium	Low	High
Health care	Low	High	Low	High
Transportation	Low	Low	Low	High
Communication & Media	High	Low	High	High
Construction	Low	High	Low	Medium
Government	High	Medium	High	High
Education	High	Low	High	High

Penetration:

High

Medium

Low

Figure 9 -Different levels of penetration of Data Analytics in various sectors

ECG, for instance, has extensively been used in clinical environments to collect the heart's electrical signals, and calculate heart rate using reliable algorithms. So, it is not in the use of data/signals that the innovation lies. Rather, the transformation of biomedical engineering and similar fields stems from the accessibility, miniaturization, and reduced cost of technologies that now enable the capture of more and more physiological data, in a wider and wider variety of environments. For instance, rather than using an ECG to track heart rate outside of clinical environments, a PPG can be placed in a device as simple as a watch, to perform the same task. To track motion, Inertial Motion Units (IMUs) are widely used to track position and orientation. And this significant increase in data available has unlocked, for researchers and clinicians, new ways of obtaining insights with analytics.

CHAPTER 3

METHODOLOGY

1. Introduction

An ideal solution to our challenge would look something like the diagram in figure 10. After breaking up our proposed IoT-based solution into its constituents, this thesis will involve the processing, and analysis of the data collected from Things, to answer the question of whether we get obtain relevant insights from that data. In our proposed architecture, this computational load would be in our Edge, but for this thesis, the aim is to develop the required algorithms.

Among the Things, in the IoT architecture, will be our e-Gloves. Here, the challenge is the accurate and reliable collection of the relevant data. So, there is a need to look at what types of movement need to be captured, and what types of sensor would be needed to achieve the latter.

Figure 10 -Proposed architecture

2. Project aims

Circling back to a previous point, the screening process for the motor symptoms of Parkinson's disease involves quite a few hassles such as travelling and suboptimal frequency of monitoring. And we do know that what is being observed during a UPDRS-III session are motor symptoms. So, the question is the following: can we

capture the same information that a neurologist may observe remotely, using motion sensors? And if so, can we migrate the UPDRS-III screening to non-clinical environments? This question can be broken down into four parts.

1. How can we use wearable devices and sensors to capture PD phenomena?
2. Once gathered, can we use that data to come up with useful insights?
3. Can we implement these devices in an architecture that facilitates their use?
4. And, most importantly, how much compliance can there be in the use of these devices?

The answer to 2) will constitute the essence of this thesis.

For the capture of phenomena in PD, e-textiles have been used in electronic gloves (e-gloves). These will constitute elements of our Things layer and will be discussed in more depth in chapter 3. In the latter, we will also discuss signal processing and analytics methods used to obtain useful information from the data collected from our e-textiles.

3. Data Collection

3.1 Experimental Design

This section describes the process of obtaining relevant data by capturing sensor signals from our e-textiles during UPDRS-III exercises. We have collected data from 10 PD-affected participants, 5 males and 5 females, with ages ranging from 49 to 76. We have

also collected data from 8 healthy participants, aged between 21 and 73 [Table 1]. Additional PD data was also available from previous work [Abtahi].

After consent (and going through a cognitive assessment test, in the case of subjects with PD), participants are asked to wear the e-gloves, and sit comfortably, back straight, in a chair. They are guided through the UPDRS-III exercises by an Android app that goes through them sequentially, while demonstrating the exercise using an animated image. This app is also connected via BLE to the e-textiles used in this study, and logs the data being collected while the exercises are being performed. We have selected six UPDRS-III exercises that the participants will perform during the experiment:

1. *Hands on thighs (time, 10 seconds):*

The participant is asked to sit in a chair, hands on thighs, and remain still. This exercise is meant to observe **rest tremor amplitude**.

2. *Arms stretched out (time, 10 seconds):*

The participant is asked to stretch out their arms forward, with straight wrists and palms down, and remain still. This exercise is meant to observe the **postural tremor of hands**.

3. *Finger to nose (time, 10 seconds):*

With the arm starting from an outstretched position, with the index finger pointing forward, the patient is asked to place their index finger on their nose, then place their hand back to the initial position. The manoeuvre is performed repeatedly. This exercise is meant to observe the **kinetic tremor of hands**.

4. *Finger tapping (time, 10 seconds):*

The participant is asked to repeatedly tap their index finger on the thumb as quickly and as widely as possible. This exercise is meant to observe the **speed and amplitude of tapping, hesitations and halts in tapping, and a decrementing amplitude.**

5. *Closing and opening grip (time, 10 seconds):*

The participant is asked to make a fist, with their palms facing downward. The participant then repeatedly alternates between having their hands closed and opened, as fast and as widely as possible. This exercise is meant to observe, again, **speed, amplitude, hesitation, halts, and decrementing amplitude**

6. *Hand flipping (time, 10 seconds):*

With arms stretched forward, and fists facing down, the participant is asked to turn their palm up and down alternately, as fast and as widely as possible. This exercise is meant to observe **speed, amplitude, hesitation, halts, and decrementing amplitude.**

Table 1-Participant's demographics

Participants with PD			Healthy Participants		
Participant	Age	Gender	Participant	Age	Gender
1	76	Female	1	73	Male
2	73	Female	2	37	Male
3	73	Female	3	27	Male
4	71	Male	4	25	Male
5	70	Male	5	22	Male
6	69	Male	6	21	Female
7	67	Male	7	21	Male
8	63	Female	8	21	Male
9	52	Female			
10	49	Male			

Now that each of the motor exercises have been looked at, how will our process allow up to retrieve information similar to what a physician might get? First, let's describe the design of the e-gloves. That is, let's survey the technology to see what set of sensors have been chosen for them. Then, we'll compare what information they can provide to us, to all the information mentioned above. Additionally, we will describe the set of signal processing and data analytics methods.

3.2 e-Glove Design

To interact with the outside world and process information, the glove uses a microcontroller. The microcontroller of choice for this project is the BLE Nano. The BLE Nano (or Nano, for short) is equipped with the Nordic nRF15822, that runs at 16 MHz, and has BLE (Bluetooth Low Energy) compatibility. The board can be configured to have six analog pins, that enables input from the outside world. Connected to these analog pins are five flex sensors. Along with our set of flex sensors, the board is also connected to an Inertial Measurement Unit (IMU). Figure 10 shows two different iterations of the glove's design. The list of UPDRS exercises has shown the need to measure finger movement, hand movement, and different types of tremor. What do these sensors do, and can they provide us with that information?

Figure 10 -Design of Smart Glove

Top image shows an older iteration of the glove, enabling to see how the sensors are embedded.

Bottom two images show current design of glove.

Starting our survey with the flex sensors, a simple way to describe them is as flexible potentiometers. Potentiometers are resistors with variable resistance and are widely used in electrical systems to measure mechanical movement. By connecting a fixed-value resistor in series with the potentiometer between a DC voltage source and ground — thus forming a voltage-divider circuit, the voltage between the two resistors will vary as the potentiometer's resistance changes. The flex sensor varies its resistance by using a conductive ink that changes resistance when its surface area varies [Langford]. To

capture any changes in the angle by the Nano, a constant resistance of 20 kilo-ohms is added in series circuit with the flex sensor. When flat, its resistance is about 10 kilo-ohms. When bent at a 90-degree angle, the resistance increases to roughly 70 kilo-ohms [Fig.11]

Figure 11 -Flex sensor illustrated here, as its resistance changes as it bends.

This range of voltages is then digitally mapped between values ranging from 0, when the resistance is at the minimum, to 1023, when the resistance is at the maximum. In the design of the glove, these flex sensors are each aligned with one finger, as well as the thumb. This placement of the flex sensors enables the proper quantification of finger movement during UPDRS tasks involving the use of fingers (finger tapping, open/close hand).

The flex sensors alone do not yet make it possible to measure all the parameters mentioned earlier. Besides finger movement, we need to know the position and movement of the hands. This is where the IMU comes in. The IMU is a set of sensors that can measure inertial movement. Among the metrics it can measure are acceleration

and angular velocity, in 3 dimensions each (the IMU also acts as a magnetometer, but that feature will not be used). The IMU, then, measures the hand's acceleration and orientation.

Table 2 gives a summary of how our chosen set of sensors can allow us to measure the types of parameters that a neurologist would investigate during a screening session. As shown, the chosen set of e-textiles is capable of measuring those metrics. This should enable us, through signal analysis, to extract specific features that could potentially indicate the presence of Parkinson's disease.

4. Signal Processing

The signals captured by the e-textiles are not of much use by themselves. In fact, they might look like noise to the naked eye. For the signals to be of use, the relevant features first had to be extracted from it. But the data cannot immediately be run through our set of algorithms. First, the data needed to be organized and pre-processed in preparation for the analysis, to make the results more reliable. Issues such as an inconsistent sampling rate or the presence of noise needed to be fixed. Additionally, some additional signals were obtained through transforming some of the original signals when relevant. So, this section will cover the methods used to remove unwanted elements of the signals collected by the sensors, as well as those used to obtain additional information that was needed. All the tools discussed were implemented using MATLAB with the necessary toolboxes.

Table 2 -Assessment of sensor selection when compared to parameters

Parameter observed by clinician	UPDRS-III Task(s)	Relevant Sensor(s)
Rest tremor amplitude	Hands on thighs	IMU
Postural tremor in hands	Arms stretched out	IMU
Kinetic tremor in hands	Finger to nose	IMU
Speed	Finger tapping, opening and closing grip, hand flipping	Flex sensor, IMU, pressure sensor
Amplitude	Finger tapping, opening and closing grip, hand flipping	Flex sensor, IMU, pressure sensor
Hesitation	Finger tapping, opening and closing grip, hand flipping	Flex sensor, IMU, pressure sensor
Halts	Finger tapping, opening and closing grip, hand flipping	Flex sensor, IMU, pressure sensor
Decrementing amplitude	Finger tapping, opening and closing grip, hand flipping	Flex sensor, IMU, pressure sensor

4.1 Preparing the Data

When acquiring data, there is often a possibility that signals end up being nonuniformly sampled. In our case, due to the occasional packet loss during data transmission, the sampling rate of the signal has been inconsistent. To get around this issue, the data is resampled to obtain a consistent sampling rate. Given the relative low frequency of the movements performed during our experiment, along with the known range of frequencies of other phenomena such as tremor, all the information wanted can be expected to be below 15 Hz. The signals have all been resampled at 128 Hz, which would be more than required to prevent any aliasing. To further avoid any aliasing, we introduce an anti-aliasing filter to band-limit the signals. The data was then saved in an organized structure to make it easier to work with. Figure 12 shows the structure of our data. This makes iterating through all the sensors' data more manageable for every exercise.

4.2 Processing the data

When the sensors are collecting data, there is always a multitude of phenomena that occur simultaneously. Thus, a lot of information relating to different events get picked up at the same time. In the data we have gathered, there are components related to voluntary movements such as during the UPDRS-III tasks, and others that are related to symptoms of PD, such as tremor and other involuntary movements. What component is considered the signal of interest, and which one is considered noise has determined what signal-processing techniques were used. Table 3 summarizes the signal-processing

techniques used in each of the tasks before proceeding to the analytics, as well as signal components of interest. The tools to implement these techniques are all available in the MATLAB environment.

Figure 12 -Structure of data, healthy vs. PD affected

In some exercises, such as *finger tapping*, and *open-close grip*, finger movement is the main criteria, and was recorded by the flex sensors. The main frequency from tapping will be dominant relative to the action tremor frequency. Specifically, for this project, we will consider this tremor as being part of the signal, as a feature, rather than being noise, when dealing with tasks that involve movement. The position signals obtained were directly used for feature extraction.

Table 3-Summary of Signal-Processing Methods Applied on Dataset

UPDRS-III task	Sensor(s)	Components	Frequencies	Signal Processing Method(s)
Hands on thighs	IMU	Resting tremor	3.5 - 7.5 Hz	Spectral-power analysis
		Gravity and other DC offsets	0 Hz	Removed by high-pass filter with 0.25-Hz cutoff
Hands stretched out	IMU	Postural tremor	4 - 8 Hz	Spectral-power analysis
		Gravity and other DC offsets	0 Hz	Removed by high-pass filter with 0.25-Hz cutoff
Finger to nose	IMU	Hand movement	~1 Hz	Spectral-power analysis
		Kinetic tremor	3.5 - 7.5 Hz	Spectral-power analysis
		Gravity and other DC offsets	0 Hz	Removed by high-pass filter with 0.25-Hz cutoff
Finger tapping	Flex sensors	Finger movement	< 6 Hz	Peak analysis
		Kinetic tremor	3.5 - 7.5 Hz	Spectral-power analysis
		DC offset	0 Hz	Flex sensor: Removed subtracting mean from signal IMU: Removed by high-pass filter with 0.25-Hz cutoff
Open/close grip	Flex sensors	Finger movement	< 3 Hz	Peak analysis
		Kinetic tremor	3.5 - 7.5 Hz	Spectral-power analysis
		DC offset	0 Hz	Flex sensor: Removed subtracting mean from signal IMU: Removed by high-pass filter with 0.25-Hz cutoff
Hand flipping	IMU	Hand movement	< 3 Hz	Merge accelerometer and gyroscope signals with complementary filter
		Kinetic tremor	3.5 - 7.5 Hz	Spectral-power analysis
		DC offset	0 Hz	Removed by high-pass filter with 0.25-Hz cutoff

In some other cases, some components of the signal were more desired than others. For instance, in the case of *hands on thighs*, *hands stretched out*, and *finger to nose*, tasks

mainly involving the IMU, the amount of tremor is being assessed, making it the signal of interest. In those cases, any other components were considered noise. So, the aim was to isolate the tremor-related signal components. To do so, frequency-domain analysis was selected, since the ranges of frequencies to which they belong are known. Resting tremor in PD has been reported to be in the range of 3.5 to 7.5 Hz [Salarian et al., Rigas et al.]. Postural tremor, on the other hand, is thought to be between 4 and 12 Hz. While assessing different types of tremor, voluntary movement may also be present. Here, we broke up our signals into low-frequency components (voluntary movements) and higher-frequency components (tremor). It is worth noting that the accelerometer constantly senses the earth's gravitational pull [Rigas et al.]. This can be removed by a high-pass filter with low cut-off frequency (0.25 Hz). The high-pass filter should also remove any DC bias in the signals and is used in all sets of data.

Hand flipping, and *finger to nose*, required additional signal-processing techniques. Given that the IMU give us linear acceleration and angular velocity, we needed to extract the position signal. This can be found by integrating the acceleration signal to obtain the velocity signal, then integrate the latter to end up with the position. Because the accelerometer is susceptible to vulnerable to high frequencies, this causes the position signal to contain noise due to accumulated error. So, another method to obtain the position signal, with the IMU, is to calculate the pitch and the roll. The pitch is the movement around the y-axis, and the roll around the x-axis. They can be found using the following set of equations:

$$Pitch = \frac{\sin^{-1}(Ax)}{\sqrt{Ax^2 + Ay^2 + Az^2}}$$

Equation 1-Pitch as a function of accelerometer data

$$Roll = \frac{\sin^{-1}(Ay)}{\sqrt{Ax^2 + Ay^2 + Az^2}}$$

Equation 2-Roll as a function of accelerometer data

Pitch and roll can also be calculated using data from the gyroscope through a numerical integration. The following equation can be used:

$$\theta = \theta + \omega \times \delta t$$

Equation 3- Angular Orientation as a function of angular velocity and time

Here, θ represents the angular velocity of the gyroscope, and δt is the sampling time.

Again, integration will cause any initial errors to accumulate. But, this time, we had two methods of calculating the same parameter. The idea is then to use both the accelerometer and the gyroscope, to complement each other's weaknesses. A method that can enable us to achieve this is to use a data-fusion algorithm such as a complementary filter. [Bhaskaran et al., Urdhwareshe et al.]

Figure 13 -Complementary filter combines accelerometer and gyroscope data to obtain orientation [Gui et al.]

The complementary filter [Fig. 13] combines low-frequency accelerometer data —to mitigate the effect of high-frequency noise, with the high-frequency gyroscope data — to mitigate the effect of high-frequency drift, to give an all-pass estimate of the orientation. Figure 13 illustrates the workings of the filter. The orientation (pitch, roll) θ is given by using the following:

$$\theta_{angle} = \alpha * (\theta_{angle} + \omega_{Gyro} * dt) + (1 - \alpha) * a_{Acc}$$

Equation 4 -Angular orientation using complementary filter

where α is the filter coefficient, ω_{Gyro} represents the angular velocity, and a_{Acc} the angular position obtained from using the previously presented trigonometric relations in equations 1 and 2. α , the filter coefficient, can be obtained from the filter's time constant, τ , through this equality [Gui et al.]

$$\alpha = \frac{\tau}{\tau + \delta t}$$

Equation 5 -Filter coefficient as a function of the time constant

The optimal value for τ can be found in an iterative manner, until the desired output is obtained.

5. Feature Extraction and Learning

The next following step in the process was then to examine the clean and organized data and try to come up with ways of extracting information. As already mentioned, certain characteristics of signals, such as frequency ranges, are well known and can be exploited as an attempt to discriminate between signals of different nature. There exist numerous methods for analyzing, not only biomedical signals, but all signals in general. Some are implemented in the time domain, some in the frequency domain, and others will make use of both. What makes a set of possible approaches better than others will always depend on the characteristics of the signal at hand. It then becomes very important to carefully examine the signal when choosing which approach(es) to take when performing the analysis, to ensure the validity of any insights that may be obtained from the analysis. In our case, dealing with biomedical signals, we have decided to take both time and frequency domain approaches to treating our signals.

Figure 14 -Spectrogram of hand-flipping movement

x-axis: frequency; y-axis (left): time; y-axis (right): amplitude color code

Figure 14 shows a spectrogram that was computed in MATLAB from a sample of our data set. This instance of the data was during a hand-flipping task. As shown here, the spectrum of the signal is not exactly consistent over time. Due to this, studying the frequency will require some time-frequency methods. Among the methods available, a simple one is to use a sliding window that segments the signal into shorter durations, during which the characteristics of the signal tend to be less random, or at least less unpredictable. All the UPDRS-III exercises in our experiments have lasted for 10 seconds.

In contrast, figure 15 shows another example of a spectrogram, this time obtained from finger-tapping signal. This time, there is less changes observed in the frequency domain over time, although not entirely static.

Figure 15 -Spectrogram of finger-tapping

x-axis: frequency; y-axis (left): time; y-axis (right): amplitude color code

Regarding our selection of features, we have chosen some in the time domain, such as mean, and variance of phenomena, or others like spectrum quantification. Table 4 lists the features used in our study. [Salarian et al. van den Noort et al.]

Table 4 -Set of features chosen

UPDRS-III task	Sensor(s)	Interest	Features
Hands on thighs	IMU	Rest Tremor	Energy at dominant frequency in spectrum; energy in low and relatively high frequency ranges; RMS* of signals
Hands stretched out	IMU	Postural Tremor	Energy at dominant frequency in spectrum; energy in low and relatively high frequency ranges; RMS of signals
Finger to nose	IMU	Kinetic tremor	Energy at dominant frequency in spectrum; energy in low and relatively high frequency ranges; RMS of signals; statistics of pitch and roll signals, such as mean amplitude and variance
Finger tapping	Flex sensors	Finger movement	Amplitude of tapping and its statistics such as mean, variance, and frequency. Velocity estimate through first difference, its statistics; energy in other sensors
Open/close grip	Flex sensors	Hand movement	Amplitude of grip movement and its statistics such as mean, variance, and frequency. Velocity estimate through first difference, its statistics; energy in other sensors
Hand flipping	IMU	Hand movement	Velocity amplitudes and energy. Pitch and roll, variations in amplitude and power, their means and other statistics.

*RMS $\rightarrow$ Root Mean Square

A sliding-window approach was taken to extract the features [Fig. 16]. That is, for every 10-second signal, the appropriate set of features has been extracted for each of several 1.5-second overlapping time windows.

Figure 16 -Sliding-window approach [Choné]

To validate the quality of these features, we have used MATLAB to build binary classification models based on them. The accuracy of our model shall serve as validation metrics for the chosen set of features. The label for each data point in the feature table is whether they have Parkinson's. The classification model chosen was based on Support Vector Machines.

Support Vector Machine

A Support Vector Machine (SVM) is a classifier defined by a separating hyperplane that acts as a separator for two or more sets of data points that belong to different categories. That is, given one labeled set of data (labels corresponding to the categories to which the data belong), the SVM model computes and outputs a hyperplane that can categorize a different set of labeled data, with the same categories involved. It does so while at the same time finding the maximum margin between the boundaries of each category [Fig. 17].

Figure 17- 2D SVM illustration [Drakos]

In the case when the hyperplane generated is linear, the SVM model is referred to as a linear SVM. Not all data is linearly separable, however. When a higher-order hyperplane is needed, other SVM models do exist such as the quadratic SVM and cubic SVM, corresponding to quadratic and cubic (polynomial) hyperplanes, among others. This is referred to as the kernel of the SVM. [Hamel] Other kernels exist other than polynomial, such as Gaussian.

A binary SVM is one in which only two categories are being separated, as in the case of this project. The two categories being, again, PD and non-PD. We will only consider the polynomial kernel case.

CHAPTER 4

RESULTS & DISCUSSION

The features were used to make a feature table to train SVM models. Table 5 shows the results obtained from the process.

Table 5 -SVM classification results

Task	Best Polynomial Kernel	Accuracy
Hands on thighs	Quadratic	81.0%
Arms stretched out	Cubic	89.2%
Finger to nose	Cubic	92.0%
Finger tapping	Linear	99.3%
Open/close grip	Quadratic	90.5%
Hand flipping	Cubic	90.6%

Lowest-degree Kernel chosen when same accuracy reached by multiple Kernels

Although these could be considered satisfactory, classification accuracy results don't necessarily tell the full story. We will, thus, discuss the results for each task in the following section, by observing a couple of the features selected, and try to make sense of them.

Hands Resting on Thighs

During this task, the participants remained seated, with their hand resting on their thighs. Observing the spectrum of the signal over time was the approach to trying to identify indication of Parkinson's from the data. Several features have been selected and computed before being tried in a few classifiers.

Figure 18 -Hands-on-thighs features observed in 2D

x-axis: energy at frequencies above 3.5 Hz, y-axis: energy at dominant frequency

red represents PD, blue represents healthy subjects

Figure 18 shows a scatter plot of the data points for PD and healthy participants. The red dots represent PD, and the blue ones healthy. This plot shows that PD patients, as expected, tend to have more energy in the frequency ranges of 3.5 to 7.5 Hz. This is expected, as this is the reported frequency range for PD resting tremor. The plot also shows a larger amount of energy at the respective dominant frequencies for PD and healthy participants. Again, since no activity is expected other than tremor in the case of PD participants, this result is expected.

The SVM model learned from our feature set was able to successfully classify Parkinson's patients and healthy subjects 81.0% of the time with a quadratic polynomial kernel. Accuracies of 71.7% and 70.6% were obtained with a linear and cubic SVM, respectively. Figure 19 shows the confusion matrix corresponding to the quadratic-SVM model. In the case of binary classification, a confusion matrix shows how many positives and negatives have been correctly or incorrectly classified. In this figure and in all subsequent confusion matrices, "1" represents PD and "0" represents healthy. As we can see, most PD data have been correctly classified as such, while most of the misclassification, relative to correct classification, comes from healthy data being classified as PD. This can be explained by noise being picked up by the IMU while at rest. If the noise happens to be in the frequency range of PD resting tremor, the model assumes that those values belong to PD data, as it was selected as one of the features.

Figure 19 -Confusion matrix for hands-on-thighs task (quadratic SVM)

Hands Stretched Out (89.2%, cubic/linear)

This task is like the hands-on-thighs task, in the sense that the participant stays at rest. The only difference being that the hands are stretched out while maintaining a pose, as opposed to resting on a surface. The features observed for this task are also the same. Figure 20 again shows that more high-frequency energy is present for PD patients. Although, a lot more overlap is observed during this movement, since it is more difficult to stay fully at rest while stretching one's arm out, compared to resting one's hands on a surface.

Figure 20 –Arms-stretched-out task features observed in 2D
x-axis: energy at frequencies above 3.5 Hz, y-axis: energy at dominant frequency
red represents PD, blue represents healthy subjects

The SVM model was able to successfully classify PD and healthy 89.2% of the time with a cubic SVM (same accuracy reached with linear). The confusion matrix in figure 21 shows again that, relative to the number of data points correctly classified as being from one category, most of the classification comes from healthy being classified as PD. Along with the reasons mentioned for this in the hands-on-thighs task, this may occur due to actual movement happening while a healthy participant attempts to keep his/her arms still while in the stretched out position.

Figure 21-Confusion matrix for arms-stretched-out task (quadratic SVM)

Finger to Nose

Very different from the two previously discussed UPDRS-III tasks, this one involved movement of the hands/arms originating from voluntary movement, besides the ones coming from tremors. Regarding the latter, frequency ranges known for tremor were still investigated for features. Here, we've also looked at the pitch and roll of the IMU to quantify voluntary movement.

Figure 22 –Finger-to-nose task features observed in 2D

*x-axis: energy at frequencies below 3.5 Hz, y-axis: RMS of the roll signal
red represents PD, blue represents healthy subjects*

In figure 22, we can see that healthy participants tend to have more energy from voluntary movement (x-axis), and more energy in general (y-axis), when compared to PD patients. This is expected, as healthy participants tend to show more range of movement during the task. The few outlier data-points (close to zero for both features shown) could be due to the beginning and end of the exercise, while the exercise was not being performed. The classification learner was able to classify PD and healthy 92.0% of the time, for both quadratic and cubic SVM models.

Figure 23 -Confusion matrix for finger-to-nose task (quadratic SVM)

Looking at figure 23, we can see that all the misclassification comes from healthy subjects being misclassified. This could be because healthy participants are potentially performing the tasks at less than their maximum capability. Or, simply, the outlying data could be having an effect of the model's training.

Hand Flipping

This task had features similar to those of the finger-to-nose task. The main difference being that we are observing movement around a different axis. Pitch becomes the main indicator, as opposed to roll. Although we can notice a lot of overlap in Figure 24, we can also see some distinctions. Looking at the range of the pitch, most of the lower values tend to be from PD data points, and most of the higher values, from healthy data points. This is expected, based on what was observed during the experiments. The same tendency can be observed in the y-axis, the RMS of the pitch.

Figure 24—Hand-flipping task features observed in 2D

x-axis: range of the pitch signal, y-axis: RMS of the pitch signal

red represents PD, blue represents healthy subjects

A cubic SVM model was able to successfully distinguish PD data points from healthy data points 90.6% of the time. Similar levels of misclassifications can be noticed between PD and healthy in the confusion matrix shown in figure 25.

Figure 25 -Confusion matrix for hand-flipping task (cubic SVM)

Finger tapping (99.3% linear)

During this task, finger movement was mostly observed. Analysis involved the index and ring fingers, as well as the thumb. A few of the features observed were tap frequency, mean of tap amplitude, and variance of tap amplitude. Figure 26 shows, for example, that healthy participants tend to not only perform wider taps than PD patients, but they also perform more taps overall, when asked to tap as quickly and widely as possible.

Figure 26 –Finger-tapping task features observed in 2D

x-axis: Mean-amplitude of taps, y-axis: frequency of taps

red represents PD, blue represents healthy subjects

A linear SVM was enough to reach an accuracy of 99.3% with our selection of features, with clearly not much misclassification occurring for the finger-tapping task.

Open/Close Hands

Very much like the finger-tapping task, this exercise mainly involved the movement of fingers, again. As well, similar features were extracted from the signals as the ones from finger-tapping. In figure 27, we can see a clear distinction between PD and healthy categories through the two features of the combined signal means of the fingers and thumb (sum of the three signal's respective means), as well as the energy present in the movement of the thumb. That is, healthy participants seem to always display more of either feature, if not both.

An accuracy of 90.5% was reached by both a quadratic and cubic SVM. Figure 28 shows the confusion matrix associated with the quadratic SVM model. Almost all misclassifications come from healthy data points being labeled as PD by the model. This could potentially be explained, again, two reasons mentioned earlier for some of the previous tasks. One being that participants may not be performing the task to the best of their ability. The other that the misclassified data points were obtained from periods of inactivity in the signal, such as at the edges.

Figure 27 –Open/Close-grip task features observed in 2D

x-axis: Mean-amplitude index, thumb, and ring, combined

y-axis: RMS of estimated velocity signal of thumb

red represents PD, blue represents healthy subjects

Figure 28 -Confusion matrix for open-close-grip task (cubic SVM)

CHAPTER 5

CONCLUSION AND FUTURE WORKS

This thesis is focused on the analysis of the movements of fingers, as well as hands, for the quantification of motor-symptoms markers for Parkinson's Disease during the UPDRS-III screening process. Innovative smart gloves were developed to record the relevant data for both hand and finger movements.

To properly capture the wide variety of phenomena that occur during the select set of tasks, flex sensors were embedded into the smart gloves to record finger movement. Along with the flex sensors, an Inertial Measurement Unit was used to record the positioning of the hands in space. This glove was designed with the goal of potentially migrating part III of the UPDRS exam from the typical clinical setting to non-clinical environments such as the patient's home. To validate the gloves, participants were respectively monitored by the smart gloves while performing UPDRS-III exercises. The data acquired from the experiments was then processed and analyzed to extract various features for each exercise. Those features were then used to build a learning table for SVM classification. Classification accuracies ranged from around 81.0% to 99.3%. Table 6 shows some of the features that were deemed relevant for each task.

Table 6 -Most relevant features per UPDRS-III task

<i>Task</i>	<i>Most relevant features</i>
Hands on thighs	<ul style="list-style-type: none"> - Energy in the 3.5+ Hz frequency range - Energy at the dominant frequency - RMS of IMU data
Arms stretched out	<ul style="list-style-type: none"> - Energy in the 3.5+ Hz frequency range - Energy at the dominant frequency - RMS of IMU data
Finger to nose	<ul style="list-style-type: none"> - Energy in the 1 – 3 Hz frequency range - RMS of IMU data - RMS of the roll
Finger tapping	<ul style="list-style-type: none"> - Energy in the 3.5+ Hz frequency range - Mean amplitude of taps - Variance of tap amplitude - Frequency of taps - RMS of velocity of finger movement - RMS of IMU signal - Number of peaks in finger position signal (not the same as number of taps)
Open/close grip	<ul style="list-style-type: none"> - Energy in the 3.5+ Hz frequency range - Mean amplitude of taps - Variance of tap amplitude - Frequency of taps - RMS of thumb position signal - RMS of velocity of finger movement - RMS of IMU signal
Hand flipping	<ul style="list-style-type: none"> - Range of the pitch - RMS of the pitch - Number of peaks in pitch, or flip frequency - RMS of IMU data

The findings shown in table 6 seem to be in agreement with the current literature regarding the motor symptoms of Parkinson's. PD patients seem to perform movements more slowly and with more variability than healthy participants, in general. They also display more movement energy at rest, related to tremor. This thesis was, however, just

one of many steps required to achieve the goal of migrating UPDRS-III screening. It would require an organized and efficient architecture [Fig. 29] to achieve the latter, as well as, crucially, some level of compliance from the end user. The following few paragraphs will discuss potential improvements and future works.

First, the MATLAB scripts developed for this work were only the first iteration of algorithms for our e-textiles data. Neither the efficiency nor the computational load of the code have been evaluated. This will represent an important step, given that these algorithms will need to be deployed in an IoT architecture. Specifically, the aim is to run them on an Edge device. Another consequence of this need for deployment is that the algorithms will need to be converted from MATLAB to a language that is more adept to Edge computing (such as Java or Python).

The next point is regarding the quality of the data collected itself. That is, the design of the e-textiles could be made more robust for better quality of data. Here are a few issues that came up during the data collection process:

- Loose boards, causing a lot of noise in IMU data
- Suboptimal glove fitting, which can create inconsistencies in finger-movement readings
- Bluetooth connectivity issues, affecting accuracy of data sent vs data collected.

Some improvements have already been made as this is being written, resolving some of the issues already. Such improvements are also necessary to increase the granularity of PD symptoms assessment by the smart glove.

Figure 29 -Full IoT architecture

Furthermore, the SVM classifiers built for this thesis were able to distinguish between healthy and PD data points, despite “noise” in the signal caused by issues brought up in the previous paragraph. In the long run, however, the goal will be to assess PD symptoms with 5 levels of severity (0 to 4). Reducing the inconsistencies in the data, thus, becomes crucial.

Going back to the architecture shown in figure 29, an important aspect not to be neglected is the presence of the physician in the process. The involvement of physicians will be crucial in the development of this IoT infrastructure. A web portal could

potentially be a great medium to enable collaboration between researchers and physicians. Through this portal, physicians can provide researchers with UPDRS scoring for our data, using the recording of the data collection sessions. Researchers, on the other hand, can provide physicians with useful analytics, which they can both use and help evaluate.

Last but not least, a crucial aspect of this architecture is the compliance of PD patients. So, one of the future stages of this project will involve a compliance study with the end users to investigate the usability of the e-textiles and the IoT architecture in non-clinical settings. Using the e-textiles for symptom assessment, then, needs to be made as simple as possible. This brings up the need to automate the process of performing the UPDRS-III tasks through our Edge device. So, one of the next stages will require the development of a closed-loop systems that automatically detects the beginning of exercises and stores the data adequately.

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