Motor Exercise Classification using machine learning

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Abstract*—Parkinson's disease has no known cure, but there do exist treatment plans which help those affected to slow the progression of the disease. These treatments are determined by the doctor's subjective observations of the patient during clinical visits. However, these visits are limited to just a few times a year. This paper attempts to migrate the subjective observations to objective measurements through the use of a smart glove and an Android application. In order to prove out this concept, the exercises are first tried with people who have not been diagnosed with Parkinson's disease. We recruited 10 people to perform six hand exercises as specified by the Unified Parkinson's Disease Rating Scale (UPDRS). Our goal is to classify each of these six hand exercises using traditional machine learning techniques. We achieved 90% accuracy in the classification of the six exercises.

Keywords*—Parkinson's, Machine learning, Motor classification, e-textiles.

Introduction

There are nearly 1 million people in the United States and more than 6 million people worldwide affected by Parkinson's disease (PD) (Parkinson's); this project aims to classify Unified Parkinson's Disease Rating Scale (UPDRS) motor exercises performed with e-textiles. These textiles are capable of being incorporated into the treatment plans for at-home therapy. Individuals with Parkinson's disease experience tremors, rigidity, slowness of movement, and difficulties with walking and driving. Currently, these individuals are required to visit the doctor's office every 4-6 months for consistent reassessment regarding the progression of the disease. This allows the provider to observe an exercise regimen involving movements such as finger tapping and hand flipping. The performance of these exercises assists the attending care team in personalizing the therapy plan. The current screening process leaves the performance evaluation subjective to the doctor watching the individual.

This work addresses developing classification methods for these aforementioned exercises, via textile sensors, integrated with Bluetooth Low-Energy communication for data recording. These sensors, which are slipped into gloves, utilize a companion Android application. The ultimate goal is to allow the care team to make data-driven decisions regarding PD therapies without the patient needing to visit the clinic more often. Currently, this work will guide our experimental setup to conduct further research into persons diagnosed with PD by first using healthy patients as a control group while focusing solely on successfully classifying hand exercises and performing offline hand exercise classification techniques.

I. Background

Parkinson's disease is a neurodegenerative disease that occurs when the brain cells which produce dopamine die and it can be seen through a constellation of movement and non-movement symptoms associated with the presence of Lewy bodies in the brain. These Lewy bodies are an abnormal clumping of protein alpha-synuclein which be expressed in a variety of diseases not just PD (Lang & Lozano, 1998). This can make the diagnosis for PD difficult since it can be easily confused with dementia with Lewy bodies. However, muscle rigidity, tremors, gait, and fine-motor control show first in the early stages of PD unlike the others (Lang & Lozano, 1998). And hand motor exams such as finger tapping and fist open/close have a special significance in the clinical assessment of the disease.

A. *Diagnostic Screening - UPDRS Part III*

A standard clinical assessment tool to evaluate and diagnose Parkinsonism – a collection of signs and symptoms of Parkinson's disease -- is the Unified Parkinson's Disease Rating Scale (UPDRS). It has four components however we focus on only the Motor Examination section which includes

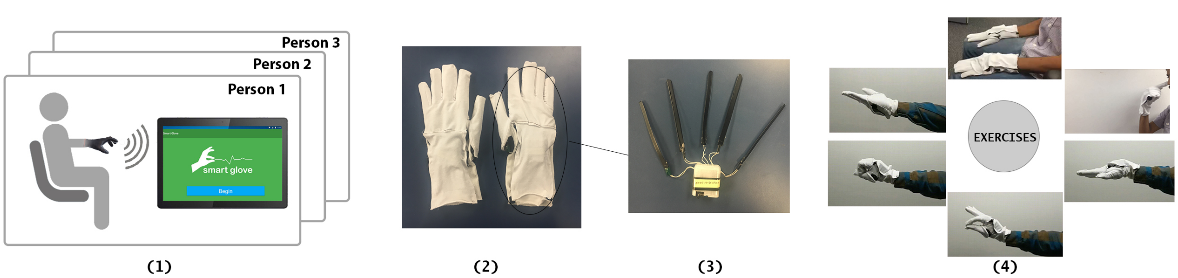

Figure 1:(1) Shows the patient and the android app used to collect data.(2)(3) Smart gloves made for patients (4) Six UPDRS exercises.

finger taps, hand movements, pronation/supination, postural tremor of hands, kinetic tremor of hands, rest tremor amplitude and constancy of rest tremor exercises. It has a scoring range from zero (0) to four (4) to scale the results of exercises (Goetz et al., 2008). The frequency of UPDRS screening varies based on the progression of the disorder but is on average 2-3 times a year.

B. ***Current Technologies for Parkinson's Disease***

Currently, there exist efforts to improve PD monitoring by tracking the hand motion of PD patients (Rodriguez-Blazquez et al., 2013; Shulman et al., 2016). The home accessible tools being researched include inertial motion monitoring of the limbs (Shulman et al., 2016) and angular measurements in the fingers (Bhaskaran et al., 2017). Overall, each of these studies incorporated the sensors into and gloves to maintain a close intimate connection to the body. The most similar technology found was created by Connolly et al. whom developed an electronic goniometric glove which is sensor based for clinical finger movement analysis (Connolly et al., 2018). They focused on arthritis and arthritis measurements with gloves. To measure the orientation and biomechanical parameters of each finger segment, IMUs are located on each of the phalanges for each finger totaling 15 IMUs. They compared their glove with 5DT Data Glove for accuracy and repeatability. They claimed that their system has comparable repeatability and better accuracy. There also exists a commercialized product with the same aim of measuring tremor in the hands; the Kinesia ONE. The Kinesia ONE is a ring-type wearable device worn on the tip distal phalange of the index finger for the side that is most affected by PD.

II. MATERIALS:

The Smart glove system provides an in-home motor examination monitoring and data analysis services for patients diagnosed with PD. This smart glove system is built in two parts as described below. First is the smart glove, a wearable e-textile and second is the companion Android app.

A. ***Smart Glove:***

This Smart glove e-textile consists of a low power nRF51822 system on a chip (SoC) with a 10 bit ADC to convert analog signals to digital signals coming from five flex sensors attached to the five fingers on the glove. The flex sensors are configured in a voltage dividing circuit. The glove also contains a LSM9DS1 Inertial Measurement Unit (IMU) -- with a triaxial ±16g accelerometer, triaxial ± 2000 DPS gyroscope and triaxial magnetometer on a chip.

The data records are a combination of flex and IMU values. The data can be reliably sent and received at a rate of 312 Bps. Each packet sent from the glove contains two bytes from each flex sensor and two bytes from each IMU reading. This provides us with an average sampling frequency of 78Hz.

B. ***Android Application:***

The Smart glove app was developed for the collection of UPDRS motor exercise data. This app has three main parts:

- Bluetooth connectivity: This app is capable of handling multiple Bluetooth connections to different devices such as the left and right glove at the same time. Before the user starts the exercises the application checks for the Bluetooth connection of both gloves and notifies the user when both devices are connected.
- Exercise fragments: The app has a built-in routine of exercises which allow the user can tap on the next button in order to switch from one exercise to the next. If the user feels they performed the exercise improperly then they can tap on the retry button.
- Data collection: A timer is implemented for ten seconds for each exercise. When the timer starts data is collected logged into a comma-separated values(CSV) file for each exercise and each hand separately. When the timer stops the user is progressed to the next exercise. Each patient has a unique ID number and all patient data files are stored in their own folder.

C. ***Software***:

In addition to the above mentioned materials, we also use MATLAB in-order to conduct our analysis and run our machine learning experiments..

IV. EXPERIMENTAL METHODS:

All experiments were performed in Wearable Biosensing Lab at the University of Rhode Island.

Figure 2: Patient using the app for data collection

A. ***Population:***

Ten subjects were recruited for conducting our experiments. These subjects were between the ages of 18-20 years. All subjects were healthy patients.

B. ***Protocol:***

Data from six hand exercises were collected via the Smart glove app. Each exercise was done for ten seconds using both left and right hands at the same time, except finger to nose which was done with one hand. A video is shown to each patient before starting each exercise which is in-built in the Smart glove app. Data from only the right hand was considered to do all our experiments to maintain a balanced control group as finger to nose is done with one hand only. Each exercise description is given as follows.

- Resting hands on thighs: In this exercise the patient rests his/her hands on their thighs
- Holding hands out straight: Patient hands are positioned at shoulder level holding them straight 90 degrees to the ground.
- Finger tap: Here index and thumb are taped together big and fast.
- Close grip: This exercise requires both hands to open and close like a grip including all fingers.
- Hand flip: One eighty degrees rotation of both hands is done in both exercises.
- Finger to nose: Here the patient touches their nose with their index finger and then touches a single point specified by the experiment conductor it could be the conductor's finger or a point on the screen.

C. **Analysis:**

C1. **Sensor selection:**

In order to conduct our analysis, sensors for each exercise were selected based on information received from each sensor. For some exercises flex sensors were more important than IMU and vice-versa due to their nature of motion. For example: for the finger tap exercise we selected index and thumb finger based on the movement of the two fingers during the exercises similarly we selected important sensors for all the exercises as shown in the table no. 1.

IMPORTANT SENSOR VALUES

Exercise Names	Important device	Thumb	Index	AccX	AccY	AccZ	GyrX	GyrY	GyrZ
Hands Hold Out	IMU		✓			✓			
Finger to Nose	IMU		✓	✓					
Finger Tap	Flex	✓	✓						
Close Grip	Flex	✓	✓						
Hand Flip	IMU						✓		
Resting Hands-on Thighs	IMU			✓			✓		

Table no. 1

C2. **Peak analysis:**

Each peak represents one finger tap for example as seen in figure no. 3 the patient is doing eighteen finger taps since there are eighteen peaks. In the finger-tapping exercise, we analyze the number of taps, the time between taps as well as the amplitude of the taps to validate our data in the flex sensors.

In order to maintain a consistent sampling rate of 128Hz, we interpolate all signal values to 1280 samples. We observe here that upsampling introduces some noise and therefore we apply a low pass filter to restore the original signal. Here in fig. no. 3 we use an infinite impulse response (IIR) low-pass filter with a passband frequency of 16Hz in-order to prevent distorting of the signal. The IIR was used to compensate for time delay by applying zero-phase filtering with a transition band steepness of 0.5.

C3. **Frequency analysis:**

Here we can observe that when a high frequency component is convolved with a low-pass filter then the noise is reduced; this can be seen as the smooth line at around 53 Hz on the X-axis in figure no. 4. This is due to the fact that very high values are

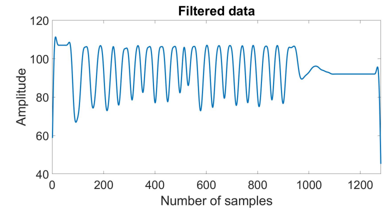

Figure 3: Graph showing filtered Finger tap data for index finger left hand.

multiplied by very low values of the filter and thus resulting in lower aptitude.

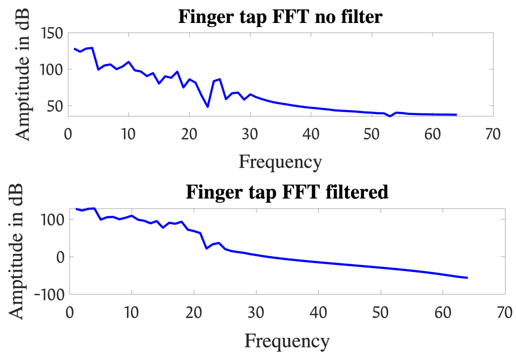

Figure 4: Graphs showing FFT's of filtered and original data.

C4. **Feature extraction:**

Features from Frequency, Time and the Statistical domain were selected to discriminate between the six exercises effectively. In order to calculate the statistical features such as maximum, minimum, variance we took these values of each sensor from each exercise of the patient. As for the frequency domain, a Fast Fourier Transform was applied to each signal and the maximum Frequency to calculate the dominant frequency. Other Frequency domain features were Dominant Frequency Magnitude (DFM), Mean frequency, Median frequency. Time-domain features were also used such as Power (P), Bandwidth(BW), Variance in Peak, Maximum peak, Minimum peak.

FEATURES

Frequency	Time	Statistical
Dominant Frequency(DF)	Power(P)	Maximum Value
Dominant Frequency Magnitude(DFM)	Bandwidth(BW)	Minimum Value
Mean frequency	Variance in Peak	Variance
Median frequency	Max Peak	
	Min Peak	

Table no. 2

C5. **Machine learning (ML):**

In order to select the best combination of features, we performed several trials in which we ran multiple classifiers for each combination of features. These classifiers are as follows K-nearest neighbors (KNN), Linear Discriminant Analysis (LDA), Naive Bayes (NB), Decision Tree (DT), Support Vector Machines (SVM). Also, we performed a hyper-parameter search using a two-fold cross-validation technique in order to prevent overfitting.

CLASSIFICATION ACCURACY

Exercises Classified	Classifier	Score(%)	Features Used
6	Coarse Gaussian SVM	61.7	3(DF, P, Var)
6	Gaussian SVM	75	2(DF, Var)
6	Quadratic/Cubic SVM	83.3	3(DF, Var, MeanF)
6	Quadratic SVM	85	5(P, DF, Var, MeanF, MedianF)
6	Linear SVM	90	(DFM,DF,P,MeanF,BW,MaxP, MeanP,VarP, Max value, Min Value,Variance)

Table no. 3

CONFUSION MATRIX

Predicted Class →

True Class ↓	Closed Grip	Finger Tap	Finger to Nose	Hand Flip	Hands Hold Out	Resting hands on thighs
Closed Grip	100%					
Finger Tap	10%	80%		10%		
Finger to Nose		10%	70%	10%	10%	
Hand Flip				100%		
Hands Hold Out		10%			90%	
Resting Hands on Thighs						100%

Table no. 4

V. CONCLUSION AND DISCUSSION:

What we found was that the simplest of classifiers do the best when it's given a set of features that capture the diversity of movements. This can be seen in the Linear SVM which shines the best with an accuracy of 90%(table no. 3). These motor exercises are versatile in nature and therefore we need a diverse set of features to classify these exercises.

As per the above confusion matrix (table no. 4) 10% of the time the classifier classifies finger to nose as finger tap - this is due to the movement similarity of exercises. In both the exercises the index finger is bent simultaneously. 10% of the time holding hands out is classified as finger tap because sometimes patients do very small finger taps and the classifier is not able to detect this feature. Movement of exercise is largely noted by observation as performed by the patient during the time of the experiment.

Statistical features such as maximum-minimum helped us differentiate between when movement is being done and when it's not. For example, to differentiate between finger tap and close grip, the maximum and minimum values of the ring finger will be very different from those of the ring in the close grip. This is because in the finger tap the ring finger is not used at all.

VI. FUTURE WORK:

We intend to collect data from PD patients. These patients will perform exercises specified by the UPDRS. These exercises will be scored by the doctor according to the UPDRS rating scale and an average of these scores will be taken in order to determine the stage of PD. Then this dataset will be combined with a healthy patient dataset and will result in the classification of PD v/s healthy patients.

REFERENCES:

1. Parkinson's 101." The Michael J. Fox Foundation for Parkinson's Research | Parkinson's Disease. Accessed August 01, 2019. https://www.michaeljfox.org/parkinsons-101.
2. Bhaskaran, K. A., Nair, A. G., Ram, K. D., Ananthanarayanan, K., & Vardhan, H. R. N. (2017). Smart gloves for hand gesture recognition: Sign language to speech conversion system. *International Conference on Robotics and Automation for Humanitarian Applications, RAHA 2016 - Conference Proceedings*. https://doi.org/10.1109/RAHA.2016.7931887. "
3. JConnolly, J., Condell, J., O'Flynn, B., Sanchez, J. T., & Gardiner, P. (2018). IMU Sensor-Based Electronic Goniometric Glove for Clinical Finger Movement Analysis. *IEEE Sensors Journal*, *18*(3), 1273–1281. https://doi.org/10.1109/JSEN.2017.2776262
4. Goetz, C. G., Tilley, B. C., Shaftman, S. R., Stebbins, G. T., Fahn, S., Martinez-Martin, P., … Zweig, R. M. (2008). Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale presentation and clinimetric testing results. *Movement Disorders*, *23*(15), 2129–2170. https://doi.org/10.1002/mds.22340
5. Lang, A. E., & Lozano, A. M. (1998). First of Two Parts. *N. Engl. J. Med.*, *339*, 1044–1053.
6. Rodriguez-Blazquez, C., Rojo-Abuin, J. M., Alvarez-Sanchez, M., Arakaki, T., Bergareche-Yarza, A., Chade, A., … Martinez-Martin, P. (2013). The MDS-UPDRS Part II (motor experiences of daily living) resulted useful for assessment of disability in Parkinson's disease. *Parkinsonism and Related Disorders*, *19*(10), 889–893. https://doi.org/10.1016/j.parkreldis.2013.05.017
7. Shulman, L. M., Armstrong, M., Ellis, T., Gruber-Baldini, A., Horak, F., Nieuwboer, A., … Martinez-Martin, P. (2016). Disability Rating Scales in Parkinson's Disease: Critique and Recommendations. *Movement Disorders*, *31*(10), 1455–1465. https://doi.org/10.1002/mds.26649