Objective Quantification of Upper Extremity Motor Functions in Unified Parkinson's Disease Rating Scale Test

Xiaoqing Jia, Nathalie Duroseau, Vivian Chan, Christina Ciraco, Rui Wang, Sarah Mostafa Nia, Kayla Ho, John P. Govindavari, Farshid Delgosha, *Member, IEEE,* Thomas Chan, Kathleen Mangunay Pergament, Bhuma Krishnamachari, and Aydin Farajidavar, *Member, IEEE*

***Abstract*— Two tri-axial accelerometers were placed on the wrists (one on each hand) of the patients with Parkinson's disease (PD) and a non-PD control group. Subjects were asked to perform three of the upper extremity motor function tasks from the Unified Parkinson's Disease Rating Scale (UPDRS) test. The tasks were: 1) finger tapping, 2) opening and closing of palms, and 3) pronation-supination movements of the forearms. The inertia signals were wirelessly received and stored on a computer for further off-line analysis. Various features such as range, standard deviation, entropy, time to accomplish the task, and maximum frequency present in the signal were extracted and compared. The results showed that among the studied population, "standard deviation", "range", "entropy", "time" and "max frequency" are the best to worst features, respectively, to distinguish between the non-PD and PD subjects. Furthermore, using the mentioned features, it is more probable to distinguish between the non-PD and PD subjects from tasks 2 and 3 as opposed to task 1.**

I. Introduction

Parkinson's disease (PD) is the second most common neurodegenerative movement disorder in the United States [1]. The prevalence of PD is rising and the disease currently has no cure [2]. The disorder is complex and progressive with diverse clinical features, typically characterized by tremor, rigidity (limb and muscle), akinesia/bradykinesia and postural imbalance [1, 3]. Treatment of those suffering with PD has mostly been focused on medication and surgery. Medication, the standard mode of treatment, tends to lose its efficacy over time, has side effects, and is not effective in treating all PD symptoms [4]. Surgery, such as deep brain stimulation, may be an option for a few selected patients, but has strict eligibility criteria and is also not effective in treating all PD symptoms [5].

The availability of tools for monitoring the functional status of PD patients is limited. The Unified Parkinson's Disease Rating Scale (UPDRS) is the most widely used scale for assessing functionality of PD in clinical research studies [6]. The UPDRS tool consists of of four parts with a total summed score: I) Non-motor Experiences of Daily Living, II) Motor Experiences of Daily Living, III) Motor Examination, and IV) Motor Complications. Each part includes several items. The response to each item can be divided into five levels with uniform anchors of 0_normal, 1_slight, 2_mild, 3_moderate, and 4_severe. The tool relies on a combination of patient self-report and the visual assessment of the patient performed by an individual trained in administering the UPDRS [7]. Although the UPDRS is a validated scale, the scoring, particularly during the motor examination component, is inherently subjective due to its reliance on the rater's visual judgment of impairments in PD patients.

With recent advances in miniaturized sensor technologies, researchers have investigated inertial sensors (such as accelerometers and gyroscopes) to objectively asses the PD motor symptoms. Initial reports suggest that such assessments for tremor and other types of motor impairment may be positively correlated with UPDRS rater assessment [8-10]. Until recently, however, the technology was not adequate to clinically study these methods. Most existing studies have been conducted on limited numbers of PD patients and have tried to utilize machine learning algorithms to assess the feasibility of using accelerometer data to estimate the severity of the motor complications in patients [11, 12]. Studies conducted on larger sample sizes have focused exclusively on PD patients with no comparisons with healthy individuals [13]. In addition, a clinically deployable hardware and software system (KinesiaTM, CleveMed) has also been developed. However, this system is relatively bulky which may limit its utility [8].

In this study, we conducted a subset of Part III of the UPDRS, the Motor Examination portion, for the upper extremity using two tri-axial accelerometers embedded in wristwatches and worn on the subjects' wrists. We collected data from both PD and non-PD subjects. Data were analyzed and features were extracted to investigate statistical differences between the performances of the two groups.

Research supported by the "Institutional Support for Research and Creativity" (ISRC) Grant through the New York Institute of Technology.

X. Jia(e-mail: xjia01@nyit.edu), R. Wang (e-mail: rwang14@nyit.edu), K. Ho (e-mail:kho02@nyit.edu), and A. Farajidavar (corresponding author: 516-686-4014; fax: 303-555-5555; e-mail: afarajid@nyit.edu) are with the Integrated Medical Systems (IMS) Laboratory at the School of Engineering and Computing Sciences, New York Institute of Technology (NYIT), Old Westbury, NY11568 USA.

S. Mostafa Nia, is with the IMS Laboratory and with the College of Arts and Sciences at the New York Institute of Technology (NYIT), Old Westbury, NY 11568 USA (e-mail: smostafa@nyit.edu).

F. Delgosha, is with the School of Engineering and Computing Sciences, New York Institute of Technology (NYIT), Old Westbury, NY11568 USA (e-mail: fdelgosh@nyit.edu).

N. Duroseau (e-mail: nduros01@nyit.edu), V. Chan (e-mail: vchan@nyit.edu), C. Ciraco (e-mail: cciraco@nyit.edu), J. Govindavari (e-mail: jgovinda@nyit.edu), T. Chan (e-mail: tchan02@nyit.edu), K. Pergament (e-mail: kpergame@nyit.edu), B. Krishnamachari (e-mail: bkrishna@nyit.edu) are with the College of Osteopathic Medicine, New York Institute of Technology (NYIT), Old Westbury, NY 11568 USA.

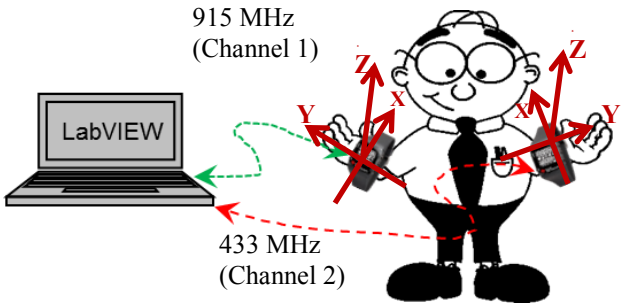

Fig. 1. The block diagram of the system used for data collection is shown. Dashed- and dotted-lines represent wireless communications between the wristwatches and the computer in 915 MHz and 433 MHz frequencies.

II. Methodology and Experimental Procedures

A. Hardware and System

Two ez430-Chronos wristwatches (Texas Instruments), which feature a 96-segment LCD display, an integrated pressure sensor, and a three-axis accelerometer, were used in this study. The BMA250 (Bosch Sensortec) [14] sensors that are designed for measuring low-g acceleration are used in ez430-Chronos. The BMA250 has a programmable measurement range of ±2g, ±4g, ±8g, and ±16g. We programmed the watches to have the range of ±2g; hence the resolution was obtained as 3.9 mg. Each axis of the accelerometer was sampled at 20 Hz, and data was wirelessly transmitted to a computer. In order to avoid communication interference, one of the watches transmitted at 915 MHz (Channel 1) and the other one at 433 MHz ISM bands (Channel 2). A custom-made program was developed in LabVIEW (National Instrument) that could simultaneously and in real-time obtain, display and restore the transmitted signals from both watches (Fig. 1).

B. UPDRS and Experimental Procedure

Two groups of subjects participated in this study: non-PD (control group) subjects and PD subjects (experimental group. All subjects were asked to wear the wristwatches on their left and right hands while performing a subset of Part III of the UPDRS that involved performing the upper extremity tasks. Namely, the following tasks were performed by all subjects: 1) finger tapping, 2) opening and closing of palms, and 3) pronation-supination movements of the forearms. Each task was performed with two UPDRS trained raters, who independently provided ratings based on their visual assessment. This study was approved by the Institutional Review Board (IRB) Committee at the New York Institute of Technology.

C. Signal Processing, Feature Selection, and Statistical Analysis

The restored signals were retrieved for off-line analysis. The signals were visually truncated to only include the performed tasks, and detrended by subtracting the mean to remove the dc component. The range, standard deviation, entropy, the time period for performing each task and the frequency with the largest power were calculated and selected as the features. The first four features were directly extracted

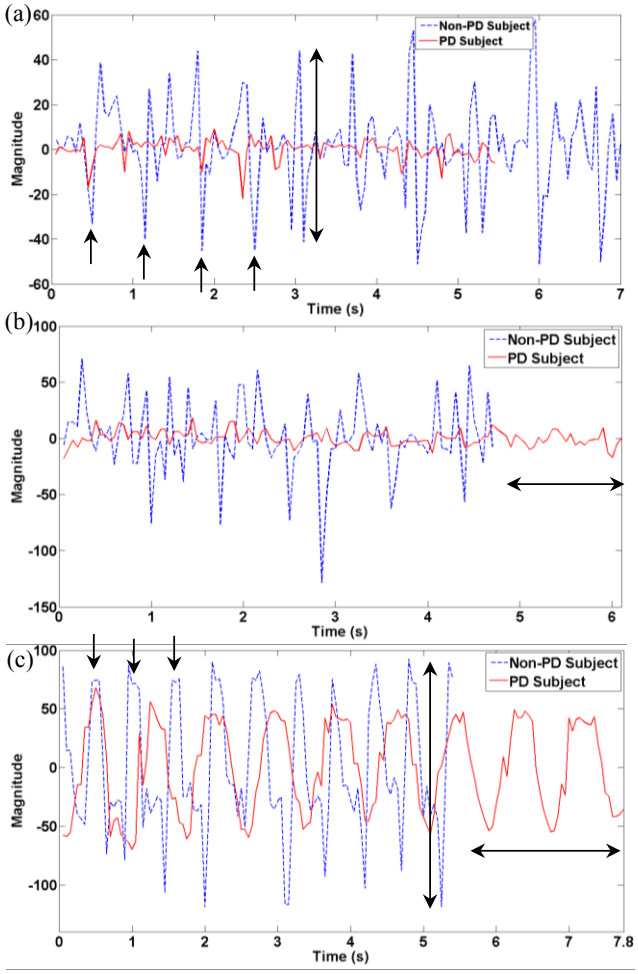

Fig. 2. (a) Shows the signals recorded from the Z axis of the accelerometer when subjects were performing task 1 with their right hand. (b) and (c) show the signals from the left hands of the subjects from Y axis and Z axis while performing tasks 2 and 3, respectively. The range of the signal variation was significantly larger for the non-PD subject in (a) and some of the peaks matched with the activity were distinguishable (arrows). It took a longer time for the PD subject to accomplish task 2 in (b). In (c), the PD subject finished the task later than the non-PD subjects, while the range of the signal was larger for the non-PD subject. The peaks of the signals in (c) matches with the number of times the subjects performed task 3. The first three peaks from the activity of the non-PD subject are indicated.

from the processed signals and the last feature was calculated from the power spectrum plots for each signal. Therefore, thirty features from X, Y, and Z axes of the left and right hands, were extracted and compared between the PD and non-PD subjects. One-way Analysis of Variance (ANOVA) was used to compare the features between the two groups (P-value < 0.05 was considered significant). The histograms of the "range", "standard deviation", and "entropy" features were calculated with ten equal-width bins and plotted as continuous graphs by connecting the centers of the bins.

III. Results

12 subjects with PD and 12 non-PD subjects participated in this study. The average and standard deviation of the subjects' age was obtained as 58.3±7.3 and 72.0±8.6 for non-PD and PD subjects, respectively.

A. Extracting and Plotting the Activities Segments

Accelerometer signals from all (X, Y, and Z) coordinates for both left and right hands of all the subjects were plotted. The signals were truncated to only include the task period; hence, the total time of each signal was extracted. Typical signals from non-PD and PD patients while performing tasks 1-3 are shown in Figs. 2 (a)-(c), respectively. Fig. 2 (a) shows the signals recorded from the Z-axis of the accelerometer, from the right hand of a non-PD and a PD subject. The non-PD subject in this case finished the task in a longer period of time than the PD subject (7.0 s vs. 5.5 s), however, the range of the signals were larger for the non-PD subject (109 vs. 31). Fig. 2 (b) depicts the Y-axis signals from the left hand of the non-PD and PD subjects. The PD subject finished the task in 6.1 s and the non-PD subject in 4.7 s. Furthermore, the range of the signals was measured as 199 and 36 for non-PD and PD subjects, respectively. Fig. 2 (c) illustrates the Z-axis signals recorded from the left hands of the subjects. In this case, the non-PD subject finished the task in less time than the PD subject (5.4s vs. 7.8s) and the range of the signals were measured as 211 and 138 for the non-PD and PD subjects, respectively.

B. Features Showed Significant Difference

The five selected features were labeled as range, standard deviation, entropy, time and max frequency. The features extracted from the PD and non-PD subjects were compared and the mean ± standard error of mean (SEM) for the features with significant differences were inserted into Tables I and II. Table I shows the mean ± SEM for the first 3 features and Table II shows for the latter two features. Each cell in the tables shows the axis that the feature extracted from and whether it was from the right hand (R) or left hand (L) of the PD (P) or non-PD (H) subjects. For instance, "RZH" and "LYP" mean that the feature was extracted from the "right hand, Z-axis, and non-PD subjects", and "left hand, Y-axis, and PD subjects", respectively.

TABLE I. MEAN ± SEM FOR TIME AND MAXIMUM FREQUENCY FEATURES

Tasks	Features	
	Time	Max frequency
1	----	----
2	LXH: 88.92 ± 2.67 LXP: 127.83 ± 17.89 LYH: 88.92 ± 2.67 LYP: 127.83 ± 17.89 LZH: 88.92 ± 2.67 LZP: 127.83 ± 17.89	LYH: 6.86 ± 0.93 LYP: 2.50 ± 0.81
3	LXH: 108.75 ± 7.93 LXP: 188.67 ± 32.81 LYH: 108.75 ± 7.93 LYP: 188.67 ± 32.81 LZH: 108.75 ± 7.93 LZP: 188.67 ± 32.81	RXH: 1.78 ± 0.14 RXP: 1.17 ± 0.19 LXH: 1.93 ± 0.17 LXP: 1.34 ± 0.19 LZH: 2.13 ± 0.29 LZP: 1.36 ± 0.20

TABLE II. MEAN ± SEM FOR RANGE, STANDARD DEVIATION AND ENTROPY FEATURES

Tasks	Features		
	Range	Standard deviation	Entropy
1	RZH:52.83 ± 8.94 RZP: 29.58 ± 4.55	RZH: 9.97 ± 1.65 RZP: 5.71 ± 0.85	RZH: 1.23 ± 0.02 RZP: 1.34 ± 0.04
2	RYH: 102.25 ± 15.61* RYP: 40.58 ± 8.77* RZH: 93.42± 6.87 RZP: 67.92 ± 8.00	RYH: 16.36 ± 3.17* RYP: 6.61 ± 1.32* RZH: 26.60 ± 3.73* RZP: 10.60 ± 1.29* LYH: 17.58 ± 2.20 LYP: 10.63 ± 2.11 LZH: 27.51 ± 2.44 LZP: 18.50 ± 3.33	RXH: 1.13 ± 0.04 RXP: 1.27 ± 0.04 RYH: 1.15 ± 0.06 RYP: 1.34 ± 0.05 RZH: 1.08 ± 0.05* RZP: 1.27 ± 0.02* LZH: 1.10 ± 0.02* LZP: 1.20 ± 0.02*
3	RXH: 218.92 ± 9.88* RXP: 124.33 ± 14.17* RZH: 158.67 ± 9.47 RZP: 129.83 ± 9.26 LXH: 237.75 ± 9.69* LXP: 155.67 ± 16.75* LZH: 195.17 ± 10.93 LZP: 150.00 ± 13.91	RXH: 64.02 ± 4.73* RXP: 28.32 ± 3.61* RYH: 12.11 ± 1.81 RYP: 7.18 ± 0.97 RZH: 46.91 ± 2.70* RZP: 35.17 ± 2.98* LXH: 71.19 ± 5.34* LXP: 38.37 ± 4.49* LYH: 17.73 ± 2.65* LYP: 9.16 ± 1.38* LZH: 59.26 ± 4.85* LZP: 39.06 ± 3.64*	LYH: 1.10 ± 0.03 LYP: 1.22 ± 0.04 LZH: 1.00 ± 0.01 LZP: 1.04 ± 0.01

* P-value < 0.01

Furthermore, all the features in both tables are paired for non-PD and PD subjects. For example, the range of the signals recorded from the Z-axis from the right hand of the non-PD subjects was significantly higher than the same signals from PD subjects (52.83 ± 8.94 vs. 29.58 ± 4.55). Empty cells in Table II mean that no significant differences were observed in any of the axes between the signals from the non-PD and PD subjects.

C. Histograms of the Selected Features

The distribution of the "range", "standard deviation", and "entropy" were plotted for all the significant axes shown in Table I. Three examples of these plots for tasks 1-3 for the "standard deviation" feature extracted from the right hand are shown in Fig. (3); (a) and (b) are from the Z-axis and (c) is from the X-axis. According to Fig. 3 (a), if we choose the standard deviation of "10" as the border between the non-PD and PD subjects, we can accurately classify 11 (out of 12) PD subjects (91.6% true positive). However, half of the non-PD subjects (6 out of 12) will also be classified as PD subjects (50% false positive). In Fig. 3 (b), if we choose "15" as the border, the PD subjects will be classified with the accuracy of 83.3% and only one non-PD subject will be classified as PD. Similarly in Fig. 3 (c), if we choose a number slightly smaller than 40 (e.g., 39) as the border, 2 of the PD patients will be classified in the non-PD category and all the non-PD subjects will be classified accurately.

IV. DISCUSSION AND CONCLUSION

In this study, we used two wireless wearable devices with tri-axial accelerometers in the form of wristwatches and asked PD and non-PD subjects to perform three of the upper extremity tasks from the UPDRS tool while wearing the wristwatches. Fig. 2 (a) showed that although the PD subject could finish task 1 faster than the non-PD subject, he did not perform the task as completely or as accurately as the non-PD subject. Features of range, standard deviation, and entropy

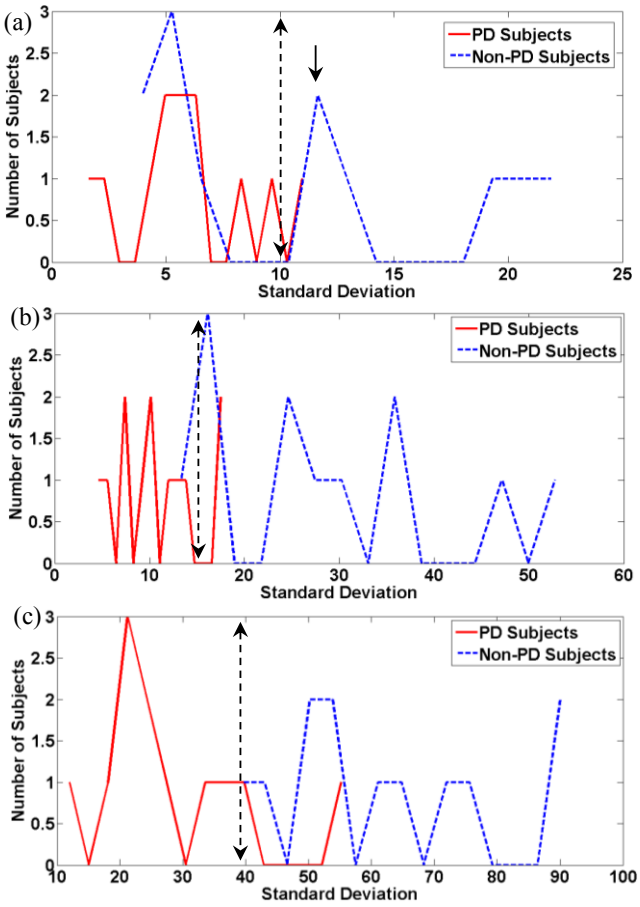

Fig. 3. The histogram of the standard deviation feature is plotted for tasks 1-3 in (a)-(c), respectively. All the plots are from the right hand. (a) and (b) are from the Z-axis and (c) is from the X-axis. The vertical dashed arrows in all the plots show possible borders between the non-PD and PD categories. The arrow in (a) shows there are 2 non-PD subjects that their standard deviation features lay in the bin centered at 12.5.

extracted from the Z-axis of the right hands showed significant difference in performing task 1 between the non-PD and PD subjects, however, the time and maximum frequency did not show any significant difference between the two groups. This can be partially due to the incomplete performance of the PD subjects or not opening their fingers as widely as the non-PD subjects.

Tables I and II showed tasks 2 and 3 could better distinguish between the non-PD and PD subjects compared to task 1. This could be due to the longer distance of the accelerometer sensor to the fingers (in tasks 1) compared to the palms (in task 2) and wrists (in task 3). In other words, task 1 and to some extent task 2 are indirectly measured by the accelerometer, while task 3 is directly measured. Fig. 2 (c) lends additional proof to this statement, since each peak in the signal matches with one iteration of the pronation-supination of the forearms and one can easily count the number of iterations performed by the subjects from the obtained signals. Tables I and II also demonstrated that among the studied population, "standard deviation", "range", "entropy", "time" and "max frequency" features are ranked the best to worst, respectively, to distinguish between the PD and non-PD subjects.

The histograms showed that the "standard deviation" feature can be used to set acceptable borders between the performance of the non-PD and PD subjects in tasks 2 and 3. However, none of the borders can provide 100% classification accuracy. Conducting more studies in the future, and separating out the subjects with various motor symptoms (e.g., subjects with tremor, stiffness, or rigidity) can potentially enhance the classification accuracy.

ACKNOWLEDGMENT

Authors would like to appreciate the support from Mr. Sim Basta from the NYIT College of Osteopathic Medicine.

REFERENCES

[1] L. De Lau, M.M. Breteler, "Epidemiology of Parkinson's disease," *Lancet Neurol.*, vol. 6, no. 5, pp. 525–535, Jun. 2006.

[2] J. W. Langston, "The Parkinson's complex: Parkinsonism is just the tip of the iceberg," *Ann. Neurol.,* vol. 59, no. 4, pp. 591–596, 2006.

[3] A. Sharma, K. Szeto, and A. R. Desilets, "Efficacy and safety of deep brain stimulation as an adjunct to pharmacotherapy for the treatment of Parkinson disease," *Ann. Pharmacother,* vol. 46 no. 2, pp. 248–254, Feb. 2012.

[4] H. H. Fernandez, "Updates in the medical management of Parkinson disease," *Cleve, Clin, J. Med.,* vol. 79, no. 1, pp. 28–35, Jan. 2012.

[5] J. M. Bronstein, M. Tagliati, R. L. Alterman, A. M. Lozano, J. Volkmann, A. Stefani, et al., "Deep brain stimulation for Parkinson disease: An expert consensus and review of key issues," *Arch. Neurol.,*vol. 68, no. 2, pp. 165, Feb. 2011.

[6] H. Tanji, A. L. Gruber-Baldini, K. E. Anderson, I. Pretzer-Aboff, S. G. Reich, P. S. Fishman, W. J. Weiner, L. M. Shulman, "A comparative study of physical performance measures in parkinson's disease," *Mov. Disord,* vol. 23, no. 13, pp. 1897–1905, Oct. 2008.

[7] C. G. Goetz, B. C. Tilley, S. R. Shaftman, G. T. Stebbins, S. Fahn, P. Martinez-Martin, et al., "Movement disorder society-sponsored revision of the unified parkinson's disease rating scale (MDS-UPDRS): Scale presentation and clinimetric testing results," *Mov. Disord.,* vol. 23, no. 15, pp. 2129–2170, Nov. 2008.

[8] J. P. Giuffrida, D. E. Riley, B. N. Maddux, and D. A. Heldman, "Clinically deployable Kinesia technology for automated tremor assessment," *Mov. Disord.,* vol. 24, no. 5, pp. 723–730, Apr. 2009.

[9] A. Salarian, H. Russmann, C. Wider, P. R. Burkhard, F. J. G. Vingerhoets, K. Aminian, "Quantification of tremor and bradykinesia in Parkinson's disease using a novel ambulatory monitoring system," *IEEE Trans. Biomed. Eng*., vol. 54, no. 2, pp. 313–322, Feb. 2007.

[10] B. Mariani, M. C. Jiménez, F. J. Vingerhoets, K. Aminian, "On-shoe wearable sensors for gait and turning assessment of patients with Parkinson's disease," *IEEE Trans. Biomed. Eng.,* vol. 60, no. 1, pp. 155–158, Jan. 2013.

[11] S. Patel, B. R. Chen, C. Mancinelli, S. Paganoni, L. Shih, M. Welsh, J. Dy, P. Bonato, "Longitudinal monitoring of patients with Parkinson's disease via wearable sensor technology in the home setting," *Conf. Proc. IEEE Eng. Med. Biol. Soc.,* pp. 1552–5, Aug. 2011.

[12] S. Patel, K. Lorincz, R. Hughes, N. Huggins, J. Growdon, D. Standaert, M. Akay, J. Dy, M. Welsh, P. Bonato, "Monitoring motor fluctuations in patients with Parkinson's disease using wearable sensors," *IEEE Trans. Inf. Technol. Biomed.,* vol. 13, no. 6, pp. 864–873, Nov. 2009.

[13] P. Bonato, D. M. Sherrill, D. G. Standaert, S. S. Salles, M. Akay, "Data mining techniques to detect motor fluctuations in Parkinson's disease," *Conf. Proc. IEEE Eng. Med. Biol. Soc.,* pp. 4766–4769, July. 2004.

[14] Bosch Sen., BMA250 [Online]. Available: https://www.bosch-sensor-tec.com/en/homepage/products_3/3_axis_sensors/acceleration_sensors/bma250_1/bma250