A Wearable Accelerometer System for Unobtrusive Monitoring of Parkinson's Diease Motor Symptoms

Faisal M. Khan
Rutgers University
New Brunswick, NJ, USA

Michael Barnathan, Michael Montgomery
BioMotion Suite, Inc.
New York, NY, USA

Stanely Myers, Lucien Côté
Columbia University Medical Center
New York, NY, USA

Sheree Loftus
Beth Israel Medical Center
New York, NY, USA

***Abstract*— Parkinson's disease is a complex condition currently monitored at home with paper diaries which rely on subjective and unreliable assessment of motor function at nonstandard time intervals. We present an innovative wearable and unobtrusive monitoring system for patients which can help provide physicians with significantly improved assessment of patients' responses to drug therapies and lead to better-targeted treatment regimens. In this paper we describe the algorithmic development of the system and an evaluation in patients for assessing the onset and duration of advanced PD motor symptoms.**

Keywords—Parkinson's, accelerometer, time series

I. Introduction

Parkinson's disease (PD) is a degenerative disorder of the central nervous system which affects the motor control of the patients it inflicts. Three of the most common symptoms are hand and leg tremors, and dyskinesia, an uncontrollable spasming/movement of the patient's upper body.

Medication for PD attempts to control these symptoms, but the frequency and dosage as well as the appropriate type of medication is often difficult to determine. Patients frequently keep track of their symptoms in inaccurate self-maintained handwritten diaries, from which physicians attempt to learn about and manage their symptoms. Assessment of PD is difficult with paper diaries as they are labor-intensive, requiring patients to self-report every half-hour, for several days in a row. For this reason, compliance tends to fall dramatically overtime. In addition, the self-assessment is frequently imprecise.

More accurate digital records of the patient's symptoms, including time, duration and intensity of onset could facilitate better disease management, as well as permit potentially dynamic adjustment of the treatment regimen. The use of accelerometers is a potential solution; however the detection of PD movement from normal signal is non-trivial. There are challenges of accurately detecting signal from background noise. Symptoms such as dyskinesia may be easily identifiable due to their drastic movements, but those such as hand tremors can be nearly indistinguishable. Finally, if digital sensors are obtrusive (in number and bodily location) and interfere with patients' daily routines, they will not be used and discarded.

In this paper we present the development of a detection system to distinguish between normal and Parkinsonian signal in the accelerometer data, as well as to classify different types of PD symptoms. We then evaluated the system in 12 patients suffering from Parkinson's disease.

II. Related Work

There has been significant work accomplished in analyzing time series data from wearable accelerometers [4, 5, 6, 9, 10, 13, 15, 16, 17]. Preece et al [16] provide a nice review of advances in the literature along with different classification methods that have been employed. Other research such as [6, 9, 15] provides detailed explanations on feature extraction methods.

There has also been work done in assessing accelerometer signals for the analysis of Parkinson's disease [2, 3, 7, 8, 11, 18]. The works by Bonato [2], LeMoyne et al [11] and Cho et al [3] in particular are notable. Commercially available device with sensor configurations on the hand, write, finger, arms, trunk, back, and/or waist [1, 12] can detect gain and postural impairments as well as tremor and dyskinesia severity. However, it has been observed that [14] such studies often are result of short monitoring periods as subjects are often required to wear cumbersome sensor configurations that are impractical in a daily life setting.

We present a system that is based on a single accelerometer worn on the waist. Additionally, while different classification methods are assessed in the literature, most of the focus has been on developing robust and informative feature extraction methodologies. Accelerometer data is often quite noisy and difficult to work with. A comparison of some of the core classification techniques has not really been present in the literature. Some recent work [12] has mentioned the use of neural networks in a 10-fold cross validation framework. We used the body of related literature as a rich resource for feature development and concentrated on comparing a set of well-known classification techniques.

III. Background

A. Equipment

BioMotion Suite's wearable system kit consists of a tri-axial accelerometer (STMicro STM33DH) worn on the subject's waist, in Sedio EVC 4g Spring Clips. The sensor

This study was sponsored by BioMotion Suite, Inc.

978-1-4799-7502-0/14 $31.00 © 2014 IEEE
DOI 10.1109/BIBE.2014.18

samples at a rate of 32 Hz, and has a range of +/- 3g. The data is processed using proprietary BioMotion Suite software developed in Matlab (the MathWorks Inc.).

B. Feature Construction

As discussed in the related work section above, and referenced in the references, there is a large body of literature on feature extraction and construction from accelerometer data, for Parkinson's disease and other applications. In our study, we concentrated on three categories of features: 1) a calculation of the moving average of the standard deviation in the accelerometer, 2) an assessment of the first peak in the signal's power spectrum, and 3) analyzing wavelet decomposition of the signal.

The moving average [6, 10, 15, 16] is a common technique for analyzing time series data that is a type of finite impulse response filter used to analyze data through averaging different subsets of the full dataset. Analyzing the moving average of the standard deviation provides a good assessment of the position and movement of an accelerometer. We employed a third party function for calculating a smoothed moving average in Matlab [19].

The second category of features we assessed was the first peak in the accelerometer's power spectral density [6, 9, 16]. In order to derive this feature, a fast Fourier transform (FFT) is performed on windowed blocks of the signal. A spectral energy is calculated, which is the sum of the squared FFT coefficients. The first peak in this power spectrum is a predictive feature in accelerometer data. We employed Matlab's "psd" and "findpeaks" functions in our study to calculate this feature.

Wavelet decomposition of the signal [15, 16] has also been proven to be a significantly informative feature in accelerometer analysis. We employed Daubechies level 5 decomposition of our accelerometer signal through the "wavedec" function in Matlab's wavelet toolbox.

IV. Classification Algorithms Evaluated

In the first round of experimentation, we evaluated six well known classification algorithms to classify normal versus Parkinsonian states in time series data from the accelerometer. The six approaches evaluated were an artificial neural network (ANN), Fisher linear discriminant (FLD), Gaussian naive bayes (GNB), logistic regression (LR), support vector machine (SVM) with a linear kernel (SVM-Lin) and a non-linear radial basis function kernel (SMV-RBF). Below is a high-level overview of all six approaches, but for more detailed and theoretical descriptions refer to [1].

A. Artificial Neural Networks

An ANN is a complex modeling approach that abstractly mimics the biological neurons in a human brain. It consists of a series of network nodes in layers which are “activated” through a mathematical function, often over a sigmoid of the form:

$$\frac{1}{1+e^{-\theta^T x}}$$

Overall, given a training set of input vectors x_n where n=1,...,N, with a corresponding set of target vectors t_n, the algorithm minimizes the error function:

$$E(w) = \frac{1}{2}\sum_{n=1}^{N} ||y(x_n, w) - t_n||^2$$

The ANN algorithm has a complex variety of options and parameters to tune the algorithm, including the number of layers, the number of nodes in each layer, the forward and backward propagation approaches during training, and much more. In this study we used the default ANN implementation in Matlab (with the Levenberg-Marquardt back-propagation method) with 3 hidden layers and 3 nodes per layer running for a maximum of 200 iterations.

B. Fisher Linear Discriminant

The FLD is a linear classification model in the context of dimensionality reduction. Consider a D-dimensional input vector x of N_1 instances of class C_1 and N_2 instances of class C_2 is projected to one dimension: $y=w^T x$. The Fisher criterion is defined to be the ratio of the between-class variance to the within-class variance. Formally:

$$w \; \alpha \; S_W^{-1}(m_2 - m_1)$$

where m_1 and m_2 are the mean vectors of the two classes:

$$m_1 = \frac{1}{N_1}\sum_{n\in C_1} x_n, \;\; m_1 = \frac{1}{N_2}\sum_{n\in C_2} x_n$$

and S_W is the within-class covariance matrix:

$$S_W = \sum_{n\in C_1}(x_n - m_1)(x_n - m_1)^T + \sum_{n\in C_2}(x_n - m_2)(x_n - m_2)^T$$

We also used the default FLD implementation in Matlab.

C. Gaussian Naïve Bayes

The GNB approach assumes the data has a Gaussian distribution. It determines the posterior class probability for each of k classes $p(C_k|x)$ using the class-conditional densities and prior probabilities by Bayes' theorem:

$$p(C_k|x) = \frac{p(x|C_k)p(C_k)}{p(x)}$$

New instances are classified to the class with the highest posterior probability.

D. Logistic Regression

LR models the posterior probability of C_1 as a logistic sigmoid acting on a linear function of the feature vector x :

$$p(C_1|x) = y(x) = \; \sigma(w^T x)$$

where $p(C_2|x) = 1 - p(C_1|x)$ and σ(a) is the logistic sigmoid function $\frac{1}{1+e^{-a}}$. In this study we employed Matlab's implementation of LR.

E. Support Vector Machines

The SVM approach is a maximum-margin classifier that transforms the data into a different dimension via a kernel function K, and then learns a decision boundary between the

classes maximizing the margin between the two classes. Given a set of input vectors x with class labels y, the following objective function is optimized:

$$\max_{b} \quad \min_{0\le\alpha_i\le C} : H = \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j K(x_i,x_j) - \sum_i \alpha_i + b\sum_i y_i \propto_i$$

given the constraints:

$$\sum_j y_j\alpha_j = 0$$

$$g_i = \sum_j \alpha_j y_i y_j K(x_i,x_j) + y_i b - 1$$

such that if $g_i \ge 0$ then $\alpha_i = 0$, if $g_i = 0$ then $0 < \alpha_i < C$, and if $g_i \le 0$ then $\alpha_i = C$. A new instance T is classified as:

$$f(T) = sign(\sum_i \alpha_i y_i K(T,x_i) + b)$$

The choice of the kernel function $K(x_i,x_j)$ and the resulting feature space is crucially interesting in theoretical and practical terms. It determines the functional form of the support vectors given the regularization parameter C and thus different kernels behave differently. Two common kernels are the linear and non-linear Gaussian or RBF:

$$\text{linear: } K(x,y) = x\cdot y \qquad \text{RBF: } K(x,y) = e^{\frac{-||x-y||^2}{2\sigma^2}}$$

In this study we employed the default Matlab SVM implementation for both kernels.

F. Multi-Class Problem

In the second round of multi-class classification we employed the traditional sequential "one-against-all" approach where multiple classifiers were trained and applied sequentially. First a model to distinguish Parkinsonian vs normal signal was developed, then the samples classified as Parkinsonian were classified by a second classifier as either dyskenisia or tremor, and finally a third classifier was employed to distinguish between hand and leg tremors.

V. Experiments and Results

There were two overall phases of this study. One was the development of the PD detection/classification system, and the second stage was the deployment and evaluation in patients. Due to difficulty in obtaining data on real patients, development was focused on signals from PD experts simulating patients, whereas final validation was on actual PD patients.

A. Developmental Data Aquisition

The dataset for this study came from expert volunteers. They all had familiarity with Parkinson's disease and observing its symptoms, but were not patients themselves.

Each simulated "patient" wore the Biomotion Suite accelerometer on the waist and was then instructed to do express certain symptoms or a normal state in mixed combinations of approximately 30 second time intervals. The states simulated included normal movement, dyskinesia, hand and leg tremors. The time interval of each state was monitored and recorded, and subsequently synchronized with the accelerometer data for activity labels at each time point.

The accelerometer was measuring signal on the x, y and z-axes once every 0.1 seconds.

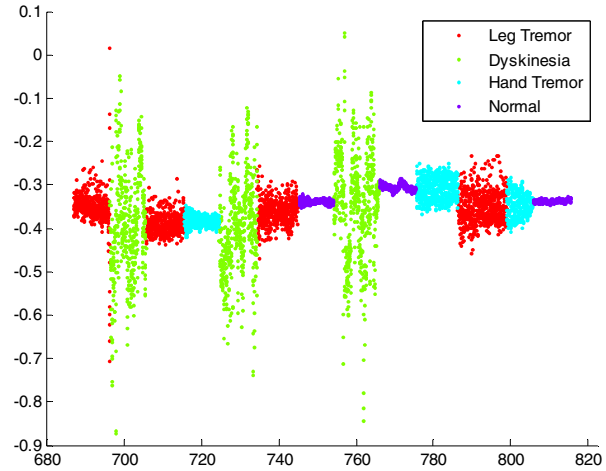

Fig. 1. Accelerometer data for a patient

Fig. 1 presents the data on an axis for one of the participants, along with the target true class labels for each time instance. In purple is a normal state, in light blue hand tremors, in red leg tremors and in green dyskinesia. It is interesting but not surprising to observe the significantly unique signature of dyskinesia, as well as the periodicity in that signal. It is also important to note the similarity between leg and hand tremors, a fact that will become significant during the second round multi-class experiments. Finally, some of the practical challenges in synchronizing accelerometer signals with their true labels can be observed around time point 690 on the x-axis, some points which are clearly dyskinesia are labeled as leg tremor and depicted in red. Luckily, such mislabels were an insignificant fraction of the data points, but do illustrate the challenges of working with real data.

B. Developmental Round 1: Two-Class Problem

In the first round of experimentation, we evaluated the six well known classification algorithms discussion above. Models were trained and tested in a standard 10-fold cross validation [1] framework. In this round of experiments, the endpoint was to determine whether each time point was exhibiting normal or Parkinsonian movement. Since the goal of this study was to evaluate machine learning methods for detecting Parkinson's disease, for the purposes of accuracy metric calculation, Parkinsonian symptoms were the positive class and normal states were the negative class.

Table I presents the total accuracy, as well as sensitivity and specificity averaged across all 10 folds for each of the six algorithms. One immediate observation is that all the methods depict good consistency for all three metrics across training and test results, indicating a lack of overfitting.

TABLE I. Performance of the six classification algorithms in the Two-Class Problem Setting

	ANN	SVM-Lin	SVM-RBF	FLD	GNB	LR
Average Training Performance Across 10 Folds						
Accuracy	76.5%	30.5%	98.6%	65.9%	82.4%	83.3%
Sensitivity	91.6%	99.8%	95.5%	60.0%	64.3%	25.1%
Specificity	72.5%	11.8%	99.4%	67.4%	87.3%	99.0%
Average Test Performance Across 10 Folds						
Accuracy	76.7%	30.4%	98.4%	65.8%	87.4%	83.3%
Sensitivity	92.0%	99.8%	95.2%	59.9%	57.9%	25.1%
Specificity	77.5%	11.8%	99.3%	67.4%	90.1%	99.0%

The best performance is exhibited by the non-linear support vector machine classifier with the Gaussian/radial basis function kernel. However the support vector machine with the linear kernel performs very poorly, likely due to significant non-linearities in the dataset. For a similar reason, the Fisher linear discriminant classifier also fares poorly.

The mediocre performance of the artificial neural network is initially surprising. However, given the complex number of parameters needed to optimally tune a neural network, investment of more optimally searching the parameter space may improve performance.

The Gaussian Naive Bayes classifier and logistic regression perform well, although interestingly enough, logistic regression tends to strongly favor specificity over sensitivity (thereby classifying most signals as normal). This bias, while not as significantly, also plagues the Gaussian Naive Bayes.

By contrast, the support vector machine with the linear kernel emphasizes sensitivity, classifying most instances as Parkinsonian. The neural network, support vector machine with the RBF kernel, and the Fisher linear discriminant function attempt to maintain somewhat of a balance across both classes.

The distribution of classes in the data is probably affecting these results to some extent. The primary purpose of the data acquisition was to obtain a good representative sampling of all three Parkinsonian symptoms and the normal state. As depicted in Fig. 1, all four classes are equally represented for the most part. However, the consequence of this data acquisition in the two-class problem space is that there is a significant imbalance in the classes, with the Parkinsonian states outnumbering the normal states 3:1. Some of the methods may perform better for balanced versus imbalanced class problems, or may need modification of parameters for such a situation.

C. Developmental Round 2: Multi-Class Problem

In the second round of experimentation, the problem was transformed into a multi-class one with the goal being to identify each time point as either normal or as a specific Parkinsonian symptom. Due to significant superiority of the support vector machine with the RBF kernel over all other approaches in the first round of experiments, only SVM-RBF was evaluated in this round.

As described earlier, in this round a sequential "one-against-all" approach was employed for classifying multiple classes. Again results were evaluated in a 10-fold cross validation framework, with the same 10 folds as from round 1. Table II presents the results of the SVM-RBF averaged across the 10 folds.

TABLE II. Accuracy of SVM-RBF in the Multi-Class Problem

	SVM- RBF
Training Accuracy	87.53%
Testing Accuracy	87.65%

The SVM-RBF approach performed well in the multi-class setting as well. However, there was a noteworthy drop in performance from the two-class problem setting. To investigate further, we observed the performance in each of the 10 folds. Tables III-XII present the classification confusion matrices of the test set for all 10 folds. In each table, the label "N" refers to the normal class, "Dysk" to dyskinesia, "HT" to hand tremor and "LT" to leg tremor. The columns represent the true classes and the rows the predicted classes.

TABLE III. Multi-Class SVM-RBF Test Classification for Fold 1

Total Accuracy:		73.7%		
	N	**Dysk**	**HT**	**LT**
N	477	4	0	8
Dysk	3	568	1	3
HT	21	3	516	560
LT	0	0	4	136

TABLE IV. Multi-Class SVM-RBF Test Classification for Fold 2

Total Accuracy:		73.8%		
	N	**Dysk**	**HT**	**LT**
N	475	7	4	3
Dysk	4	625	0	6
HT	15	1	449	561
LT	0	1	2	151

TABLE V. Multi-Class SVM-RBF Test Classification for Fold 3

Total Accuracy:		96.8%		
	N	**Dysk**	**HT**	**LT**
N	440	10	5	4
Dysk	1	638	1	4
HT	10	0	447	15
LT	6	1	16	706

TABLE VI. Multi-Class SVM-RBF Test Classification for Fold 4

Total Accuracy:		97.1%		
	N	**Dysk**	**HT**	**LT**
N	478	6	1	1
Dysk	4	589	2	6
HT	10	0	483	11
LT	13	2	12	686

TABLE VII. Multi-Class SVM-RBF Test Classification for Fold 5

Total Accuracy:		97.1%		
	N	**Dysk**	**HT**	**LT**
N	455	4	4	1
Dysk	0	622	1	6
HT	9	1	466	13
LT	5	4	19	694

TABLE VIII. Multi-Class SVM-RBF Test Classification for Fold 6

Total Accuracy:		97.3%		
	N	**Dysk**	**HT**	**LT**
N	473	5	0	2
Dysk	2	595	0	6
HT	22	0	513	5
LT	4	0	16	661

TABLE IX. Multi-Class SVM-RBF Test Classification for Fold 7

Total Accuracy:		72.5%		
	N	**Dysk**	**HT**	**LT**
N	434	3	8	11
Dysk	2	644	0	4
HT	21	3	512	580
LT	0	1	0	81

TABLE X. Multi-Class SVM-RBF Test Classification for Fold 8

Total Accuracy:		75.5%		
	N	**Dysk**	**HT**	**LT**
N	460	2	0	3
Dysk	2	592	0	7
HT	28	1	536	519
LT	0	1	2	151

TABLE XI. Multi-Class SVM-RBF Test Classification for Fold 9

Total Accuracy:		96.4%		
	N	**Dysk**	**HT**	**LT**
N	488	11	6	3
Dysk	1	571	1	4
HT	16	1	460	9
LT	8	4	20	701

TABLE XII. Multi-Class SVM-RBF Test Classification for Fold 10

Total Accuracy:		96.4%		
	N	**Dysk**	**HT**	**LT**
N	471	10	2	6
Dysk	6	622	0	5
HT	17	0	456	13
LT	5	0	19	672

As can be observed, the multi-class SVM-RBF has excellent performance in six of the ten folds. In the four folds where performance deteriorates, it is due to leg tremor being misclassified as hand tremor. As discussed earlier and depicted in Fig. 1, the accelerometer signal for leg and hand tremors appear very similar, and in some of the folds, the classes are too similar for the classifier to properly separate them.

In general however, the system appears to be doing quite well in distinguishing between normal, dyskinesia and (combined hand and leg) tremor states.

D. Validation on Real Patients

The developed multi-class algorithm was then implemented into the Biomotion Suite System Kit, and deployed to be evaluated on real patients suffering from PD. 12 patients with mid to late stage disease (ages 55 to 83) with varying degrees of symptom frequency and severity and currently prescribed Levodopa were recruited. Patients were not recruited if they did not regularly report experiencing dyskinesia after their Levodopa regimen as the physicians were interested in employing the BioMotion System to adjust the dosage and frequency of the patients' prescriptions. Each patient wore the

kit for a period of approximately 1 hour while engaged in everyday activities. The patients were also video-taped during the monitoring period. All subjects provided informed consent to participate in the study according to a protocol approved by the Institutional Review Board of the Institute for Muscular and Neurologic Function.

The accelerometer signal was correlated with observed symptoms as noted by domain experts observing the patients, and secondarily confirmed by the synchronized video recordings. Patients' states were classified as either normal, tremor (hand or leg) or dyskinesia. The overall classification accuracy was 72%, with a majority of the errors due to falsely detecting tremor. The false negative rate was low, indicating minimal missing of PD symptoms. Of interest, the frequency analysis in the power spectral density detected significant differences between tremor and dyskinesia, indicative of a difference in motor behavior between the symptoms, largely due to the periodicity of the tumor.

VI. Conclusions and Future Work

We have presented an innovative wearable and unobtrusive system for the monitoring of motor symptoms as expressed by patients suffering from Parkinson's disease. During the development of the system, we evaluated the ability of six well known and regarded machine learning classification algorithms to detect symptoms of Parkinson's disease on time-series data from a wearable accelerometer. We gathered data from simulated patients and conducted experiments in two rounds.

When we first considered a two-class formulation of the problem, the support vector machine classifier with a non-linear RBF kernel manifestly outperformed other methods. When expanded to a multi-class problem setting, the SVM-RBF continued to perform well, but struggled to distinguish between hand and leg tremors in some cases. This study suggests that the SVM-RBF is a robust method for classifying Parkinson's disease from an accelerometer signal, and likely would perform well for other accelerometer applications as well and should be considered as a possible solution.

We then validated our system on 12 patients suffering from PD. The system performed well, providing physicians with invaluable information in the onset, frequency and intensity of patients' symptoms for adjustment of their prescription.

From a developmental perspective, we plan to improve the misclassification between hand and leg tremors in the multi-class setting. In this study we limited ourselves to three categories of features for analyzing time-series/accelerometer data, and only certain types of features within these three categories. It would be advisable to consider additional features, notably of different types, to determine whether they improve overall performance, and in particular, distinguishing between hand and leg tremors. Additionally, the performance of some of the approaches, in particular the artificial neural network, may improve through more extensive tuning and optimization of the algorithm parameters.

We also plan on deploying and evaluating the system in a larger set of patients, particularly looking at the effectiveness in groups of patients prescribed with different medications, not just Levodopa, and determining the effectiveness of the system across various therapies.

References

[1] C. Bishop, Pattern Recognition and Machine Learning. Springer, 2006.

[2] P. Bonato, D. Sherrill, D. Standaert, S. Salles, M. Akay, "Data Mining Techniques to Detect Motor Fluctuations in Parkinson's Disease." 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2004.

[3] C. Cho, Y. Osaki, M. Kunin, C. Cohen, W. Olanov, and T. Raphan, "A Model-Based Approach for Assessing Parkinsonian Gait and Effects of Levodopa and Deep Brain Stimulation." Prooceedings of the 28th IEEE EMBS Annual International Conference, 2006.

[4] D. Gaurov, K. Helkala, and T. Sondrol, "Biometric Gait Authentication Using Accelerometer Sensor." *Journal of Computers*, 1:7, 2006.

[5] A. Godfrey, R. Conway, D. Meagher, and G. OLaighin, "Direct Measurement of Human Movement by Accelerometry." Medical Engineering and Physics. 30., 2008.

[6] Z. He, Z. Liu, L. Jin, and J. Huang, J. "Weightlessness Feature - A Novel Feature for Single Tri-axial Accelerometer based Activity Recognition." 19th International Conference on Pattern Recognition, ICPR 2008., 2008.

[7] J. Hoff, A. van der Plas, E. Wagemans, and J. van Hilten, J. "Accelerometric assessment of levodopa-induced dyskinesia in Parkinson's disease." Movement Disorders. 16:1, 2001, pp58-61.

[8] N. Keijsers, M. Horstink, and S. Gielen, "Ambulatory motor assessment in Parkinson's Disease." Movement Disorders, 21:1, 2006, pp34-44.

[9] M. Khan, S. Ahamed, M. Rahman, and R. Smith. "A Feature Extraction Method for Realtime Human Activity Recognition on Cell Phones." Third Third International Symposium on Quality of Life Technology (isQoLT 2011) (Toronto, Canada), June 2011.

[10] J. Kwapisz, G. Weiss, and S. Moore. "Activity Recognition using Cell Phone Accelerometers." ACM SIGKDD Explorations 12:2, 2010, pp74-82.

[11] R. LeMoyne, C. Corojan, and T. Mastroianni. "Quantification of Parkinson's Disease Characteristics using Wireless Accelerometers." ICME International Conference on Complex Medical Engineering., 2009.

[12] W. Maetzler, J. Domingos, K. Srulijes, J. Ferreira, and B. Bloem. "Quantitative Wearable Sensors for Objective Assessment of Parkinson's Disease". Movement Disorders, 28:12, 2013, pp1628-1637.

[13] M. Mathie, A. Coster, N. Lovell, and B. Celler. "Detection of daily physical activities using a triaxial accelerometer." Med. Biol. Eng. Comput. vol 41, 2003, pp296-301.

[14] M. Merello and A. Antonini. "Evaluation of Motor Complications: Motor Fluctuations". In Rating Scales in Parkinson's Disease, C. Sampaio, C. Goetz and A. Schrag Eds. New York: Oxford University Press, 2012, pp99-114.

[15] S. Preece, J. Goulermas, L. Kenney, and D. Howard. "A comparison of Feature Extraction Methods for the Classification of Dynamic Activities from Accelerometer Data." IEEE Transactions on Biomedical Engineering, 56:3 (March 2009).

[16] S. Preece, J. Goulermas, L. Kenney, D. Howard, K. Meijer, and R. Crompton. "Activity identification using body-mounted sensors - a review of classification techniques." Physiological Measurement, 2009.

[17] N. Ravi, N. Dandekar, P. Mysore, and M. Littman. "Activity Recognition from Accelerometer data." Proceedings of the 17th Conference on Innovative Applications of Artificial Intelligence (IAA), 2005.

[18] J. Weaver. A Wearable Heath Monitor to Aid Parkinson Disease Treatment. Masters Thesis. MIT., 2003.

[19] http://www.mathworks.com/matlabcentral/fileexchange/19998-fast-smoothing-function