

# on or n, ar non- D a ro, r on n, B a o ra n r n o D an no o,

Julio Vega  
University of Manchester  
julio.vega@manchester.ac.uk  
Supervised by Dr Simon Harper

## ABSTRACT

Parkinson's Disease (PD) affects patients' motor and non-motor functionality. Traditional assessment techniques are inaccurate because PD symptoms vary throughout the day and are evaluated in sporadic and subjective sessions. Although recent works have utilised wearable devices to try to overcome these issues, most are unsuitable for following patients regularly for a long time. In contrast, my approach aims to monitor PD continuously in a longitudinal, naturalistic, non-disruptive and non-intrusive way. It uses smartphones to log and transmit over the Internet social, environmental, and interaction data about patients and their surroundings. This data is complemented with other web data sources (i.e., geographical and weather data) and then processed to infer a set of metrics (a latent behavioural variable or LBV) of people's activities and habits. Then, the LBV's trends are measured and mapped to the progression of the disease. As a part of the pilot study to test the proposed methodology, I have collected  $\approx 290$  million records from 2 patients, making this dataset 34.5x bigger and 4x richer than state-of-the-art sets. I used the collected data to identify six possible PD-related LBVs. This project aims to get a more accurate disease picture and to reduce the physical and psychological burden of traditional assessment methods. Ultimately, the work has the potential to save patients' time and improve the efficiency and effectiveness of health services.

## Keywords

Parkinson's Disease; Smartphone; Behaviour Inferencing; Passive Sensing; Health Monitoring

## 1. PROBLEM

PD is a neurodegenerative disorder affecting around seven to ten million people worldwide [21]. It worsens patients' quality of life, especially in the elderly population. PD has motor symptoms such as rest tremor, bradykinesia (slow

movement) or rigidity and non-motor symptoms like cognitive impairment, behavioural and psychiatric problems or sleep disorders, among others [12].

Traditionally, the severity of PD symptoms is quantified using clinical scales during regular visits of patients to health centres [9]. However, this approach is unsuitable for long-term, recurrent monitoring because it is subjective, expertise-dependant [26, 34] and prone to recall [11, 23, 31] and cognitive bias [4]. Likewise, short assessment sessions provide an inaccurate picture of PD as its symptoms vary throughout the day [24, 25]. Moreover, it is infeasible to check a patient at a hospital every day all day. Thus, a sporadic assessment makes it difficult to tailor treatments to the patient's real condition [32, 35].

Some of these issues are tackled using electronic devices to assess PD objectively and automatically. Nevertheless, the device type, the way it is used and the chosen monitoring methodology have different outcomes. Although wearable devices are a popular choice, they are often attached to uncomfortable body locations and patients need to follow scripted assessment routines. This makes it impractical to monitor PD for a long time outside the laboratory.

I believe this can be done differently. I hypothesise that PD severity can be assessed by quantifying the disease's effects on patients' daily life activities and habits. Furthermore, such human behaviour can be inferred from data gathered with a smartphone and from complementary sources. This way, I expect to reduce the physical and cognitive burden of traditional and other technology-supported techniques by taking advantage of the smartphone's ubiquity.

## 2. STATE OF THE ART

Technology-supported PD monitoring works are objective, more concise and more precise than traditional methods. They can be ambient based (sensors installed in a room), video based (cameras recording patients) and wearable based (people porting the devices). The latter have received most of the attention because they can monitor people outside delimited areas, register fine motor body movements and can be cheaper and easier to set up.

Most wearable based approaches focus on motor symptoms like tremor [23, 35], bradykinesia [22, 23, 32, 35], gait disturbances [3, 17, 20, 35, 36], voice alterations [6, 34] or motor fluctuations [25]. Among these approaches, the use of accelerometer data has wide popularity, sometimes complemented by gyroscope data, audio recordings or video recordings depending on the monitored feature. Although several

Copyright is held by the International World Wide Web Conference Committee (IW3C2). IW3C2 reserves the right to provide a hyperlink to the author's site if the Material is used in electronic media.  
WWW'16 Companion, April 11–15, 2016, Montréal, Québec, Canada.  
ACM 978-1-4503-4144-8/16/04.  
DOI:<http://dx.doi.org/10.1145/2872518.2888598>.

of these projects have positive results quantifying PD symptoms, the monitoring methodology they use can be unsuitable for the long-term and in-the-wild assessments. This is because participants need to wear numerous devices, to carry them in uncomfortable body locations and/or to perform evaluation tasks that interfere with their daily routines.

Recently, smartphones have been used to monitor PD. For example, location data collected over eight weeks is used to calculate a metric ('lifespace') representing a person's movement patterns [16]. Other work has assessed hand tremor [5, 13, 15, 19, 30], speech [2, 30], facial tremors [30], motor activities [1], gait disturbances [2, 19, 24], upper-limb bradykinesia [27] and posture, finger tapping and reaction times [2]. They use the inertial sensors, the touchscreen or the camera of the device. Similarly to single-purpose devices, almost all identified smartphone-based projects monitor participants during a single day and/or performing short scripted tasks under (semi-)controlled conditions. Although [16] was the exception and participants were followed doing their regular activities, the authors only used one data source (GPS), finding a suggested relationship to PD clinical scores. I believe this is an idea that can be further explored and improved.

### 3. PROPOSED APPROACH

My work will monitor PD in a *longitudinal, naturalistic, non-intrusive* and *non-disruptive* way. Additionally, I will follow a *macro-scale* approach assessing trends of human activities and habits instead of measuring fine motor movements (micro-scale) which has been the focus of previous research. Furthermore, I propose to combine multiple data sources (*multi-source*) to simplify the quantification of complex behavioural features. Altogether, these six monitoring attributes are novel in the context of PD progression assessment.

I defined three research questions: *a)* Can complex human behaviour be inferred from smartphone collected data?, *b)* Can PD be monitored via such behavioural inferences?, and *c)* Can human behaviour be linked to PD severity?

My project aims to answer these questions by exploring PD progression assessment using Latent Behavioural Variables (LBV) derived from heterogeneous data. Such data is collected using a smartphone and processed to infer behavioural metrics. I define a LBV as a set of metrics that quantify a particular human activity or habit. For example, if I consider typing on the device's keyboard as an activity, I can measure patient's typing speed, halt frequency and the number of errors as determined by the use of the backspace key. These LBVs can be analysed over an extended period to identify trends and obscure outliers. Thus, the trends' changes can be mapped to the evolution of the disease. Due to the size and complexity of this problem, I will focus on a 'thin slice' identifying at least one LBV.

The objectives of the project are four. First, to analyse the available smartphone capabilities to collect heterogeneous data. Second, to conduct a pilot study to define and refine a monitoring methodology according to the project aims. Next, to explore inference techniques for determining people's behaviour based on the collected data. Finally, to analyse the relation between the found inferences and PD severity.

## 4. METHODOLOGY

I propose a four stage methodology for PD monitoring (Figure 1).

1. Data collection. Patient's social, environmental and interaction data is gathered from all the sensors and interfaces within a smartphone. This is complemented by ambient, spatial and other web data sources.
2. Data processing. Raw data is modified, filtered and ranked to reduce the complexity and dimensionality of the original dataset.
3. Data analysis. This stage has two tasks, LBV Identification and 'Profile of Living' (PL) generation. In the first one, a human activity or habit is inferred from various data sources. Then, a LBV (a set of metrics) is computed based on these inferences. During the second task, a LBV's evolution is quantified using a PL. The PL is a proposed metric created by dividing the LBV's metrics into two groups. The ones obtained from the beginning of the monitoring period produce a personal baseline while the rest are considered deviations over time. If we go back to the typing example, a decrease in typing speed after a few months of being constant could be a sign of motor deterioration.
4. Evaluation. PL variations (shifts in behaviour) are mapped to changes in PD severity and are evaluated using clinical scores produced at regular intervals (every few months) by trained staff as a ground truth. These scores will come from the Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [9] that assess motor and non-motor symptoms including activities of daily living. Currently, this scale is "accepted by the US and [the] European Union as a reliance on new drug approvals, studies on placebo response and trials of surgical interventions" [7] and is widely used as a golden reference in research projects outside clinical environments [18]. Thus, I will study the correlation of the magnitudes of PL changes of each LBV with the disease's MDS-UPDRS scores and subscores. Besides this and as a secondary measure, I will analyse the trends of the different LBV(s)' metrics, to see if their changes are related to each other and to the theoretical progression of the PD symptoms they quantify according to the literature.

I expect two main contributions from this approach. The first one is a methodology to investigate behavioural LBVs related to PD using time series data. The second one is the identification of at least one LBV. This process includes the development of the 'Profile of Living' metric and algorithms for behaviour inferencing and for multi-source time series analysis. Finally, if the LBV(s) is correlated with PD severity, this work will be a proof of concept of non-intrusive and non-disruptive PD monitoring based on passive mobile sensing.

## 5. RESULTS

To first test this methodology, I carried out a pilot PD monitoring study where 29 types of data sources (smartphone's interfaces and sensors, and web sources) were logged from two patients over 83 days using the Android app AWARE



Figure 1: Proposed methodology for PD monitoring

Table 1: Smartphone collected datasets for behaviour inferring

Dataset	Sources	R/P/Hr
D1	29	70,972
D2 [10]	1	359,243
D3 [33]	7	2,060
D4 [29]	2	12,500
D5 [28]	8	183
D6 [14]	15	44

[8] modified in-house to allow data encryption and synchronisation through the cloud service Google Drive. The resulting dataset (D1) has  $\approx 290$  million data points. In comparison to existing smartphone collected datasets (D2 & D3) for PD monitoring, D1 has a higher resolution (70,972 records per person per monitored hour (R/P/Hr)) and semantic richness (29 sources, see Table 1). This means, D1 is 34.5x bigger than D3, and although it is 5x smaller than D2, the latter has only one source. Furthermore, when compared to other smartphone datasets (D4, D5, D6) in the context of behavioural inferring (but not PD), D1 has 5.6x more R/P/Hr than the closest dataset. This approach to data collection will increase the potential for inferring complex PD-related behavioural habits.

Next, I identified six LBVs, each composed of several metrics, after analysing the collected data, the symptoms of PD [12], the assessment tasks of the MDS-UPDRS [9] and everyday human activities or habits that might be influenced by PD symptoms according to what other works have measured using alternative approaches (i.e. [5, 16]). The LBVs to consider in the future are typing patterns, phone usage patterns, episodes of going up/down stairs, participant’s indoors routine, motor activities (e.g., walking) and social patterns. Other LBVs might be identified based on the data collected in our next PD monitoring study.

The ‘social patterns’ LBV combines Bluetooth (BT), WiFi, location, spatial, calls and messages data. It has metrics like BT surrounding devices (potential indicator of human presence), communication patterns (potential indicator of a mood change), frequented places’ visiting routine (potentially related to people’s mood and physical fitness, i.e. going to a park versus a casino), among others. I preliminarily analysed this LBV using three days of data from one participant. The Figure 2a and 2b show the WiFi Access Points (AP) and the BT devices detected around the phone, respectively. In these two plots, there are two periods of  $\approx 4.5$  hrs and  $\approx 2.5$  hrs each during which the participant was outside the home. In Figure 2c, spatial data was used to infer that the patient spent his/her time at a park, a supermarket, a community centre and a residential area. In this map, the

participant’s house is identified using the phone’s last known position and three APs detected with a strong signal during the night. In the BT plot, a sporadic device was recorded while the person was at home indicating social interaction with a visitor or relative. Finally, in Figure 2d there is a list of the calls made or received by the participant, three of them placed while he/she was at home. All these parameters can be weighted and put together to generate a social interaction score.

Following a similar process, other LBVs and their metrics can be analysed. The next step is to take into account data from a longer period and study patients’ routines to then evaluate these inferences against the PD clinical scores.

## 6. CONCLUSIONS AND FUTURE WORK

The pilot results provide good evidence that PD progression monitoring based on behavioural inferences extracted from data collected using mobile devices and web data sources is feasible. Due to the exploratory nature of this work, there are several LBVs and inferences that can be analysed, all promising leads that might be related to PD severity.

The executed pilot study will serve as a source of insights and best practices for data collection and analysis for the next monitoring study. This new study is awaiting the approval of the relevant ethics committees and will include five patients monitored for 12 months.

During and after the main study, I will analyse the collected data to identify behavioural LBVs as mentioned earlier. Because human behaviour is a complex phenomenon that can be segregated and interpreted in different ways, there are many opportunities to apply techniques that have had positive results from slightly similar contexts (e.g., text mining, fuzzy logic, etc.). This is a topic I would like to discuss during my participation in the WWW Ph.D. Symposium.

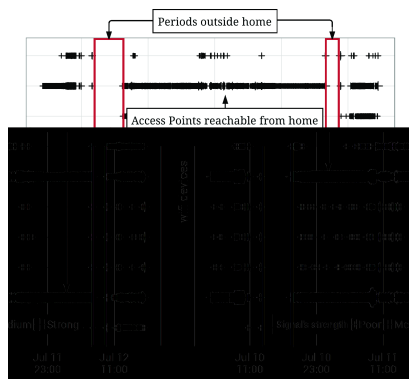
If there is a positive outcome at the end of this proof-of-concept PD monitoring methodology, future work under the same line of research could have a significant impact on the quality of life of PD patients by saving them time, reducing the physical and psychological burden related to traditional and alternative assessment methods, and improving the precision of treatments and interventions. This will help to reduce the clinicians’ workload and improve the efficiency of health services.

## 7. ACKNOWLEDGEMENTS

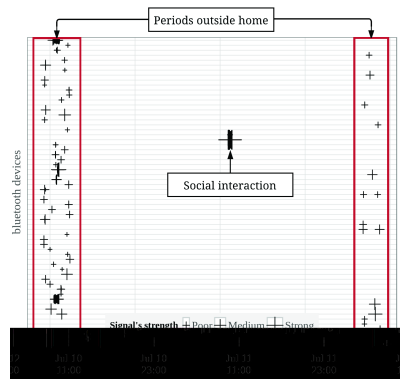
This project is sponsored by the National Council of Science and Technology (CONACyT) and the Secretariat of Public Education (SEP) of Mexico. We also acknowledge the support of the Medical Research Council Confidence in Concept (MRC CiC) scheme.

## 8. REFERENCES

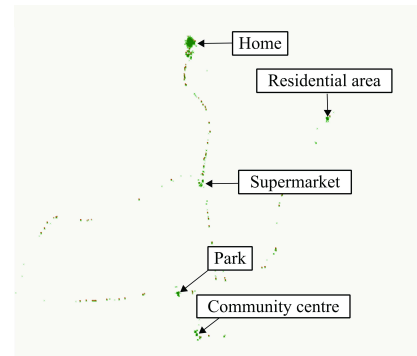
- [1] M. V. Albert, S. Toledo, M. Shapiro, and K. Koering. Using mobile phones for activity recognition in parkinson’s patients. *Frontiers in Neurology*, 3(158), 2012.
- [2] S. Arora, V. Venkataraman, A. Zhan, S. Donohue, K. Biglan, E. Dorsey, and M. Little. Detecting and monitoring the symptoms of parkinson’s disease using smartphones: A pilot study. *Parkinsonism & Related Disorders*, 21(6):650 – 653, 2015.



(a) WiFi access points scanned by the smartphone, it is possible to identify the periods where the patient was in and out their home.



(b) Bluetooth access points scanned by the smartphone, it is possible to identify the periods where the patient was in and out their home and an isolated device which could indicate social interaction.



(c) A map with the patient's location, it is possible to identify their frequented visited places.

Call	Date	Type	Duration (min)	Phone number
1	11/Jul/2015 13:56	Outgoing	3	Number 1
2	11/Jul/2015 13:57	Outgoing	10	Number 2
3	11/Jul/2015 13:59	Missed	0	Number 2
4	11/Jul/2015 19:18	Outgoing	529	Number 3
5	11/Jul/2015 19:19	Outgoing	940	Number 5
6	11/Jul/2015 20:24	Outgoing	264	Number 3

Calls placed at home

(d) Calls made and received by the patient, it is possible to identify the calls made from home.

**Figure 2: Different mobile and web data sources combined to extract information on different aspects of human social behaviour during a 3-day period for the ‘social patterns’ Latent Behavioural Variable.**

- [3] J. Barth, J. Klucken, P. Kugler, T. Kammerer, R. Steidl, J. Winkler, J. Hornegger, and B. Eskofier. Biometric and mobile gait analysis for early diagnosis and therapy monitoring in Parkinson’s disease. In *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, volume 2011, pages 868–71, Jan. 2011.
- [4] K. R. Chaudhuri, P. Martinez-Martin, A. H. Schapira, F. Stocchi, K. Sethi, P. Odin, R. G. Brown, W. Koller, P. Barone, G. MacPhee, L. Kelly, M. Rabey, D. MacMahon, S. Thomas, W. Ondo, D. Rye, A. Forbes, S. Thuk, V. Dhawan, A. Bowron, A. J. Williams, and C. W. Olanow. International multicenter pilot study of the first comprehensive self-completed nonmotor symptoms questionnaire for parkinson’s disease: The nmsquest study. *Movement Disorders*, 21(7):916–923, 2006.
- [5] J.-F. Daneault, B. Carignan, C. É. Codère, A. F. Sadikot, and C. Duval. Using a smart phone as a standalone platform for detection and monitoring of pathological tremors. *Frontiers in Human Neuroscience*, 6:357, 1 2012.
- [6] Ö. Eskidere, F. Ertaş, and C. Haniç. A comparison of regression methods for remote tracking of parkinson’s disease progression. *Expert Systems with Applications*, 39(5):5523–5528, 4 2012.
- [7] S. Fahn, R. Elton, and M. of the UPDRS Development Committee. Unified parkinson’s disease rating scale. *Recent Developments in Parkinson’s Disease*, 2:153–163, 1987.
- [8] D. Ferreira, V. Kostakos, and A. Dey. Aware: mobile context instrumentation framework. *Frontiers in ICT*, 2(6), 2015.
- [9] C. G. Goetz, B. C. Tilley, S. R. Shaftman, G. T. Stebbins, S. Fahn, P. Martinez-Martin, W. Poewe, C. Sampaio, M. B. Stern, R. Dodel, B. Dubois, R. Holloway, J. Jankovic, J. Kulisevsky, A. E. Lang, A. Lees, S. Leurgans, P. A. LeWitt, D. Nyenhuis, C. W. Olanow, O. Rascol, A. Schrag, J. A. Teresi, J. J. van Hilten, and N. LaPelle. 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, 2008.
- [10] N. Y. Hammerla, J. M. Fisher, P. Andras, L. Rochester, R. Walker, and T. Plötz. PD Disease State Assessment in Naturalistic Environments using Deep Learning. In *Conf. Innov. Appl. Artif. Intell.*, Austin, Texas, 2015.
- [11] J. Hicks, N. Ramanathan, D. Kim, M. Monibi, J. Selsky, M. Hansen, and D. Estrin. Andwellness: An open mobile system for activity and experience sampling. In *Wireless Health 2010, WH ’10*, pages 34–43. ACM, 2010.
- [12] J. Jankovic. Parkinson’s disease: clinical features and diagnosis. *Journal of Neurology, Neurosurgery & Psychiatry*, 79(4):368–376, 2008.
- [13] N. Kostikis, D. Hristu-Varsakelis, M. Arnaoutoglou, C. Kotsavasiloglou, and S. Baloyiannis. Towards

- remote evaluation of movement disorders via smartphones. In *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pages 5240–5243, Aug 2011.
- [14] J. K. Laurila, D. Gatica-Perez, I. Aad, O. Bornet, T.-M.-T. Do, O. Dousse, J. Eberle, M. Miettinen, et al. The mobile data challenge: Big data for mobile computing research. In *Pervasive Computing*, number EPFL-CONF-192489, 2012.
- [15] R. LeMoyné, T. Mastroianni, M. Cozza, C. Coroian, and W. Grundfest. Implementation of an iphone for characterizing parkinson’s disease tremor through a wireless accelerometer application. In *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pages 4954–4958, Aug 2010.
- [16] J. Liddle, D. Ireland, S. J. McBride, S. G. Brauer, L. M. Hall, H. Ding, M. Karunanithi, P. W. Hodges, D. Theodoros, P. A. Silburn, et al. Measuring the lifespan of people with parkinson’s disease using smartphones: proof of principle. *JMIR mHealth and uHealth*, 2(1), 2014.
- [17] S. Mazilu and G. Tröster. Wearable technologies: One step closer to gait rehabilitation in parkinson’s patients. *XRDS*, 21(2):48–53, Dec. 2014.
- [18] M. D. S. T. F. on Rating Scales for Parkinson’s Disease. State of the art review the unified parkinson’s disease rating scale ( updrs ): Status and recommendations. 18(7):738–750, 2003.
- [19] D. Pan, R. Dhall, A. Lieberman, and D. B. Petitti. A mobile cloud-based parkinson’s disease assessment system for home-based monitoring. *JMIR mHealth and uHealth*, 3(1), 2015.
- [20] M. Pansera, J. J. Estrada, L. Pastor, J. Cancela, R. Greenlaw, and M. T. Arredondo. Multi-parametric system for the continuous assessment and monitoring of motor status in parkinson’s disease: An entropy-based gait comparison. In *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pages 1242–1245. IEEE, 2009.
- [21] Parkinson’s Disease Foundation. Coping with a diagnosis, 2015. [http://www.pdf.org/en/newly\\_diagnosed\\_pd](http://www.pdf.org/en/newly_diagnosed_pd).
- [22] S. Patel, B.-r. Chen, C. Mancinelli, S. Paganoni, L. Shih, M. Welsh, J. Dy, and P. Bonato. Longitudinal monitoring of patients with parkinson’s disease via wearable sensor technology in the home setting. In *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pages 1552–1555. IEEE, 2011.
- [23] S. Patel, K. Lorincz, R. Hughes, N. Huggins, J. Growdon, D. Standaert, M. Akay, J. Dy, M. Welsh, and P. Bonato. Monitoring motor fluctuations in patients with parkinson’s disease using wearable sensors. *Information Technology in Biomedicine, IEEE Transactions on*, 13(6):864–873, 2009.
- [24] L. Pepa, L. Ciabattini, F. Verdini, M. Capecci, and M. Ceravolo. Smartphone based fuzzy logic freezing of gait detection in parkinson’s disease. In *10th Int. Conf. IEEE on MESA*, pages 1–6. IEEE, 2014.
- [25] C. Pérez-López, A. Samà, D. Rodríguez-Martín, A. Català, J. Cabestany, E. de Mingo, and A. Rodríguez-Moliner. Monitoring motor fluctuations in parkinson’s disease using a waist-worn inertial sensor. In *Advances in Computational Intelligence*, pages 461–474. Springer, 2015.
- [26] N. Piro, L. Baumann, M. Tengler, L. Piro, R. Blechschmidt-Trapp, et al. Telemonitoring of patients with parkinson’s disease using inertia sensors. *Applied clinical informatics*, 5(2):503–511, 2014.
- [27] B. P. Printy, L. M. Renken, J. P. Herrmann, I. Lee, B. Johnson, E. Knight, G. Varga, and D. Whitmer. Smartphone application for classification of motor impairment severity in parkinson’s disease. In *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pages 2686–2689. IEEE, 2014.
- [28] R. Rawassizadeh, E. Momeni, and P. Shetty. Scalable Mining of Daily Behavioral Patterns in Context Sensing Life-Log Data. page 10, Nov. 2014.
- [29] J.-L. Reyes-Ortiz, L. Oneto, A. Samà, X. Parra, and D. Anguita. Transition-aware human activity recognition using smartphones. *Neurocomputing*, 2015.
- [30] V. Sharma, K. Mankodiya, F. La Torre, A. Zhang, N. Ryan, T. G. N. Ton, R. Gandhi, and S. Jain. *Design, User Experience, and Usability. User Experience Design for Everyday Life Applications and Services: Third International Conference, DUXU 2014, Held as Part of HCI International 2014, Heraklion, Crete, Greece, June 22-27, 2014, Proceedings, Part III*, chapter SPARK: Personalized Parkinson Disease Interventions through Synergy between a Smartphone and a Smartwatch, pages 103–114. Springer International Publishing, Cham, 2014.
- [31] L. M. Shulman, I. Pretzer-Aboff, K. E. Anderson, R. Stevenson, C. G. Vaughan, A. L. Gruber-Baldini, S. G. Reich, and W. J. Weiner. Subjective report versus objective measurement of activities of daily living in parkinson’s disease. *Movement Disorders*, 21(6):794–799, 2006.
- [32] M. Sung, C. Marci, and A. Pentland. Wearable feedback systems for rehabilitation. *Journal of neuroengineering and rehabilitation*, 2:17, 1 2005.
- [33] The Michel J. Fox Foundation. Predicting parkinson’s disease progression with smartphone data, 2013. <https://www.kaggle.com/c/predicting-parkinson-s-disease-progression-with-smartphone-data>.
- [34] A. Tsanas, M. A. Little, P. E. McSharry, and L. O. Ramig. Nonlinear speech analysis algorithms mapped to a standard metric achieve clinically useful quantification of average parkinson’s disease symptom severity. *Journal of The Royal Society Interface*, 8(59):842–55, 6 2011.
- [35] A. T. Tzallas, M. G. Tsipouras, G. Rigas, D. G. Tsalikakis, E. C. Karvounis, M. Chondrogiorgi, F. Psomadellis, J. Cancela, M. Pastorino, M. T. A. Waldmeyer, et al. Perform: A system for monitoring, assessment and management of patients with parkinson’s disease. *Sensors*, 14(11):21329–21357, 2014.
- [36] A. Weiss, S. Sharifi, M. Plotnik, J. P. van Vugt, N. Giladi, and J. M. Hausdorff. Toward automated, at-home assessment of mobility among patients with parkinson disease, using a body-worn accelerometer. *Neurorehabilitation and neural repair*, 25(9):810–818, 2011.