2017 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)

Human Activity Recognition from Sensor-Based Large-Scale Continuous Monitoring of Parkinson's Disease Patients

Wei-Yi Cheng, Alf Scotland, Florian Lipsmeier, Timothy Kilchenmann, Liping Jin, Jens Schjodt-Eriksen, Detlef Wolf, Yan-Ping Zhang-Schaerer, Ignacio Fernandez Garcia, Juliane Siebourg-Polster, Lynne Verselis, Meret Martin Facklam, Frank Boess, Anirvan Ghosh, Thomas Kremer, Kirsten I. Taylor, Christian Czech, Christian Gossens

Pharma Research and Early Development
Roche Innovation Center Basel, F. Hoffmann-La Roche Ltd.
Basel, Switzerland

Jay Soto, Martin Koller

Prothena Biosciences Inc.,
South San Francisco, USA

Michael Grundman

Prothena Biosciences Inc.; Global R&D Partners LLC,
San Diego, USA

Andreas U. Monsch
University of Basel; Felix Platter Hospital, University Center for Medicine of Aging, Memory Clinic,
Basel, Switzerland

Ron Postuma

McGill University, Montreal General Hospital, Department of Neurology, Montreal, Canada

Michael Lindemann

Pharma Research and Early Development
Roche Innovation Center Basel;
Baden-Wuerttemberg Cooperative State University,
Loerrach, Germany

***Abstract* — Smartphone-based assessments have been considered a potential solution to passively monitor gait and mobility in early-stage Parkinson's disease (PD) patients. In the Multiple Ascending Dose clinical trial of PRX002/RG7935, 44 PD patients and 35 age- and gender-matched healthy individuals performed smartphone-based assessments for up to 24 weeks and up to 6 weeks respectively. For "passive monitoring", subjects carried the smartphone with them as part of their daily routine, while sensors in the smartphone recording movement data continuously. In total, over 30,000 hours of passive monitoring data were collected. To classify the sensor signal into activity profiles, we built a Human Activity Recognition (HAR) model using Deep Neural Networks (DNN) trained on previously published data. The activity profiles of the participants determined by the HAR model showed significant differences between PD patients and healthy controls in the percentage of time walking and frequency in which subjects changed positions (sitting and standing). This combination of sensor data and machine learning-based activity profiling was shown to hold great promise for use in future clinical practice and drug development.**

Keywords—sensors; activity recognition; wearable; cell phone; accelerometer; deep learning; Parkinson's disease; clinical trial

I. Introduction

Parkinson's disease (PD) is a degenerative disorder of the central nervous system. Motor symptoms such as tremor, rigidity and slowness of movement, are among the earliest symptoms that have an impact on quality of life and also form the basis of the clinical diagnosis. Many studies have implemented wearable systems or on-body sensors as an objective and quantifiable way to assess motor function-related impact of the disease. While historically "on-body sensors" have been widely used in the laboratory setting to evaluate PD patients' motor functions, many studies have shown that differences in gait may be more apparent in free-living conditions than in the laboratory [1]. Nowadays, most smartphones have built-in sensors to provide more environment-aware services, allowing patients to carry a smartphone around in their daily routines, while the phone records their daily activities providing a more natural way of collecting longer span of monitoring patients' daily activities. In this paper, we present the results of the first large-scale, longitudinal, free-living, passive monitoring of gait and mobility of PD patients in a clinical trial setting using smartphones. With Deep Learning, we inferred activity profiles from subjects and observed significant differences between PD patients and healthy controls (HC). The results suggest a promising future for a wider adoption of smartphone technology in diagnostic and drug development purposes.

This study was sponsored by F. Hoffmann-La Roche Ltd. (Basel, Switzerland) and Prothena Biosciences Limited (South San Francisco, CA, USA)

II. Methods

A. Data Collection

Detailed information of the PRX002/RG7935 study can be found on www.clinicaltrials.gov. Our analysis solely focused on exploring differences between HC and PD cohorts, and did not look at PRX002/RG7935-related effects. In total, 24,104 hours of passive monitoring data were recorded for the PD cohort, and 8,614 hours for the HC cohort. In line with a previously published approach [2], we filtered out accelerometer data where the standard deviation of Euclidean norm less than 0.03 m/s^2 more than 30 minutes, as during these

978-1-5090-4722-2/17 $31.00 © 2017 IEEE
DOI 10.1109/CHASE.2017.87

spans smartphones were likely not carried by the subjects. This step removed 14% of the passive monitoring data.

B. HAR

A diagram of the 9-layer neural network model structure and an example data flow is shown in Fig 1. Similar structures have been used previously for HAR and have been shown to out-perform the traditional machine learning methods [3]. Our HAR model was trained on two public data sets [4] [5] to classify six activities: walking, stairs, jogging, sitting, standing, and lying down. The continuous accelerometer data were down-sampled into 20Hz and segmented into 4-second windows with 75% overlapping with adjacent ones.

III. Results

A. Human Activity Recognition Performance Validation

To ensure the HAR model can accurately translate the sensor data into activity profile, we first analyzed the performance of the model in the held-out validation set. The HAR model was able to correctly distinguish gait activities (walking, stairs, jogging) from stationary activities (sitting, standing, lying down) with more than 98% of accuracy, Additional validation on labeled Gait and Balance data from the trial data also showed that the HAR model was able to successfully profile the Gait segments with 96.9% of accuracy, and Balance segments with 99.5% accuracy.

B. Activity Profiles Comparison

We quantified the mobility of each subject by calculating the proportion of time when the subject engaged in gait activities (walking, stairs, jogging) over the total passive monitoring coverage time of the patient. Fig 2(a) shows the overall proportion of different gait activities over the total coverage for PD and HC cohorts. In the PD cohort we detected a median of 9.7% of gait spans over all coverage spans as supposed to HC cohort's 15.1%. Fig 2(a) shows that the HC cohort had a significantly higher per-subject gait activity level than PD cohort, with Mann-Whitney test P value 2.43E-8.

C. Number of Sit-to-Stand and Stand-to-Sit Comparison

It has been observed that one manifestation of the functional impact of PD is in the sit-to-stand and stand-to-sit (STS) events [6]. From the activity profile, we calculated the coverage-normalized STS events for each subject. We observed that median number of STS per hour of PD patient was 1.44, which was significantly lower than HC subject's 1.74, as shown in Fig 2(b). Mann-Whitney test P value between two groups was 1.60E-8.

IV. Discussion and Outlook

Results from this study show that it is feasible to measure gait and mobility in early-stage PD patients using smartphone-based passive monitoring. Sensor data collected during passive monitoring provides previously inaccessible, ecologically valid insights into patients' daily behavior and functioning. A next step would be to correlate the mobility and gait features with

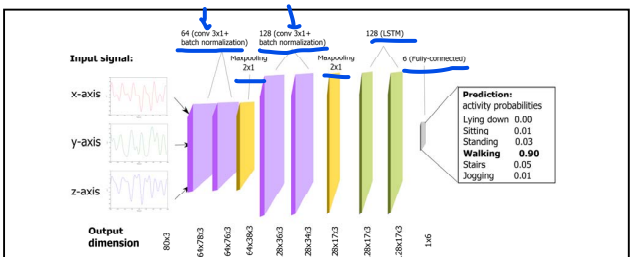

Fig. 1. Example dataflow from raw signal to activity classfication

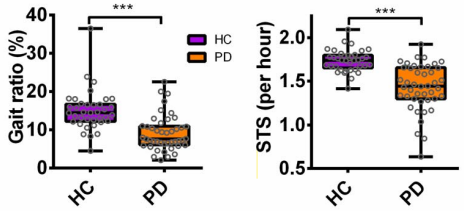

Fig 2: Associations between HAR-profiled mobility measurements and cohort in (a) Gait ratio. (b) Average STS events per hour.

the MDS-UPDRS that is used in clinics to evaluate PD severity. Further analysis into the sensor signals of gait spans might reveal more information regarding symmetry, power of stride lengths. Challenges to predict more fine-grained activities still exist, and may require incorporating different types of sensor signals from smartphones (*e.g.* gyroscope, barometers, etc.). Information from this study may be applicable to other motor function-related diseases to further understand disease progression or treatment effects.

Acknowledgment

We thank Max A. Little for his technical input at the early stages of this research project.

References

[1] S. Del Din, A. Godfrey, B. Galna, S. Lord, and L. Rochester, "Free-living gait characteristics in ageing and Parkinson's disease: impact of environment and ambulatory bout length," J. of NeuroEngineering and Rehabilitation, 2016 13:46.

[2] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan , R. Sen, "Zee: Zero-Effort Crowdsourcing for Indoor Localization," MobiCom'12, August 22–26, 2012

[3] F. J. Ordóñez and D. Roggen, "Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition," Sensors 2016, 16, 115.

[4] G. M. Weiss and J. W. Lockhart, "The Impact of Personalization on Smartphone-Based Activity Recognition," Proceedings of the AAAI-12 Workshop on Activity Context Representation: Techniques and Languages, Toronto, CA. 2012

[5] A. Stisen, H. Blunck, S. Bhattacharya, T. S. Prentow, M. B. Kjærgaard, A. Dey, T. Sonne, and M. M. Jensen "Smart Devices are Different: Assessing and Mitigating Mobile Sensing Heterogeneities for Activity Recognition" 13th ACM Conference on Embedded Networked Sensor Systems, Seoul, Korea, 2015.

[6] A. Zijlstra, M. Mancini, U. Lindermann, L. Chiari, and W. Zijlstra, "Sit-stand and stand-sit transitions in older adults and patients with Parkinson's disease: event detection based on motion sensors versus force plates", J. NeuroEngineering and Rehabilitation 2012, 9:75