SPARK: Personalized Parkinson Disease Interventions through Synergy between a Smartphone and a Smartwatch

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Abstract. Parkinson disease (PD) is a neurodegenerative disorder afflicting more than 1 million aging Americans, incurring $23 billion in annual medical costs in the U.S. alone. Approximately 90% Parkinson patients undergoing treatment have mobility related problems related to medication which prevent them doing their activities of daily living. Efficient management of PD requires complex medication regimens specifically titrated to individuals' needs. These personalized regimens are difficult to maintain for the patient and difficult to prescribe for a physician in the few minutes available during office visits. Diverging from current form of laboratory-ridden wearable sensor technologies, we have developed SPARK, a framework that leverages a synergistic combination of Smartphone and Smartwatch in monitoring multidimensional symptoms – such as facial tremors, dysfunctional speech, limb dyskinesia, and gait abnormalities. In addition, SPARK allows physicians to conduct effective tele-interventions on PD patients when they are in non-clinical settings (e.g., at home or work). Initial case series that use SPARK framework show promising results of monitoring multidimensional PD symptoms and provide a glimpse of its potential use in real-world, personalized PD interventions.

Keywords: mHealth, Smartphone, Parkinson Disease, Pervasive Healthcare, Personalized Health, Telemedicine.

1 Introduction

Parkinson disease (PD) is the second most common neurodegenerative disorder, affecting 4 million people worldwide with over 9 million PD cases being projected by 2030 [1]. Incurring $23 billion in annual medical costs in the U.S. alone and with projected increases as our population ages, there is an urgent need to improve lives and reduce costs for those afflicted with PD [2]. Currently, two major issues- complex and medication regimens and incapability of patients for frequent clinic visits hinder

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making substantial progress in improving treatments for patients with PD. A primary challenge of PD treatment is that PD progresses uniquely in each individual. A reliable, unobtrusive, quantitative tool for evaluating multidimensional disease progression such as dyskinesia, freezing of gait, disability with activities of daily life (ADL) in individuals with PD holds a great value both for clinical assessments and personalized treatments. We have designed SPARK, a Smartphone/Smartwatch system for Parkinson disease. Overarching goals of SPARK are to:

- Personalize PD management through intelligent sensing elements;
- Tele-monitor disease progression in PD patients in their day-to-day environments;
- Collect clinically relevant data to understand ADL affected by PD

In this paper we present the modular framework of the SPARK that is built on the advances in clinical practice, wearable technologies, mobile computing, machine learning, and pervasive healthcare. We present the advantages of the SPARK in comparison to research by other groups working on similar problems. We present three layers of SPARK architecture, enabling personalized patient-centered care for PD. We also provide initial results of in-lab pilot studies that used the SPARK framework to monitor multidimensional symptoms of control subjects. We conclude this paper with a summary of the presented work and a brief discussion on some challenges that are present in applicability of the SPARK framework.

2 Background and Related Work

2.1 Unified Parkinson Disease Rating Scale (UPDRS)

Unified Parkinson's Disease Rating Scale (UPDRS) that was originally introduced in 1987 [3] is now the most commonly used measure of PD progression [4]. Table 1 provides a complete list of UPDRS tests; with some of them require observations made by patients or caregivers while the rest of them need physicians to evaluate patients in clinics. The tests involve measurement of symptoms spanning from motors functions to activities of daily life to psychiatric health. Due to lack of longitudinal information of PD patients when they are in home settings, it makes it challenging for physicians to; 1) understand personalized issues of patients that occur on daily basis and; 2) make informed decisions on therapeutic or medication interventions.

2.2 Survey on the Use of Wearable Technology in PD Interventions

There are several reports of objectively monitoring movements in PD. Approaches include wearable accelerometers, gyroscopes, electromyography, doppler ultrasound, magnetic motion trackers, digital drawings, pressure-sensitive foot insoles, and passive infrared sensors placed in home [6-8]. Accelerometers (often with gyroscopes) have monitored motor aspects of PD including walking, freezing of gait, balance, falls, bradykinesia, dyskinesia and tremor [6].

Table 1. List of tests involved in evaluating PD patients with UPDRS (adopted from [5])

Part	Domain	Item ("Y" – potential use of SPARK)	Observer (Location)
I	Mentation, behavior and mood	1. Intellectual impairment 2. Thought disorder 3. Depression 4. Motivational/Initiative	Patient/ Caregiver (home)
II	Activities of Daily Life (ADL)	5. Speech (Y) 6. Salivation 7. Swallowing 8. Handwriting (Y) 9. Cutting food and handling utensils (Y) 10. Dressing (Y) 11. Hygiene 12. Turning in bed (Y) 13. Falling (Y) 14. Freezing when walking (Y) 15. Walking (Y) 16. Tremor (Y) 17. Sensory complaints related to PD	Patient / Caregiver (home)
III	Motor examination	18. Speech (Y) 19. Facial Expression (Y) 20. Tremor at rest (Y) 21. Action or postural tremor of hands (Y) 22. Rigidity 23. Finger taps (Y) 24. Hand movements (Y) 25. Rapid altering movement of hands (Y) 26. Leg agility (Y) 27. Arising from chair (Y) 28. Posture (Y) 29. Gait (Y) 30. Postural stability (Y) 31. Body bradykinesia & hypokinesia (Y)	Physician / Clinician (clinic)
IV	Complications of therapy	A. Diskinesias 32. Duration of dyskinesia (Y) 33. Disability associated with dyskinesia (Y) 34. Painful dyskinesia 35. Presence of early morning dystonia (Y) B. Clinical fluctuations 36. Are "OFF" periods predictable? (Y) 37. Are "OFF" periods unpredictable? (Y) 38. Do "OFF" periods come on suddenly? (Y) 39. What portion of day is the patient "OFF"? (Y) C. Other complications 40. Symptoms such as anorexia, nausea, or vomiting 41. Sleep quality (Y) 42. Symptomatic orthostasis	Physician / Clinician (clinic)

Of the studies in Table 2, the six highlighted studies achieved ~90% or higher accuracy in detecting movements of interest. Four of these studies demonstrate a personalized approach in placing sensors on the most affected side instead of placing sensors on the same body parts in all patients. The other two studies [9, 10] personalized their approach further by incorporating subject-specific characteristics in analyses. Keijsers et al. [9] noted that several variables were better at classifying PD movements in patients without tremor compared to those with tremor. Moore [10, 11] monitored freezing of gait, a phenomenon when gait is halted and the patient's feet are "stuck to the ground." Using the same threshold for all patients with a Freeze Index (derived from spectral analyses), 75% of gait freezes were detected. This improved to 89% when the threshold was calibrated for each subject. Together, these studies demonstrate that a personalize approach to monitoring movement performs better than a "one size fits all" approach. Our research group (Das et al. [11]) has designed machine learning approaches which can build the person specific disease progression models and reliably (more than 90% accuracy) predict "ON" and "OFF" medication state.

3 SPARK: Smartphone/Smartwatch System in PD Interventions

Currently no wearable technology is at disposal of neurologists and clinicians to effortlessly monitor PD progression when patients are in naturalistic settings. Physicians demand deployable technologies that offer longitudinal monitoring for PD interventions in non-clinical settings:

1. Passive monitoring: This is the unobtrusive collection of data without any interruption of routine behavior of PD patient. Data collection occurs in the background of day-to-day activities. For patients, passive monitoring provides a way to be monitored without interrupting routine activities or relying on abilities that may be impaired (e.g. cognition, mobility) or thinking about "being sick."
2. Active Monitoring: Active monitoring requires patients to interact with mobile screen for collecting contextual data – such as speech, facial tremors, medication intake, mood, pain, and so forth – that are experiential samples of PD progression. In contrast to passive monitoring, active monitoring allows patients to be more engaged and proactive in managing their health.

3.1 Smartwatch/Smartphone System

Recently, mobile health (mHealth) has emerged as a promising field in treating patients with advanced mobile phones (Smartphones) since smartphones come with inbuilt sensors and computing and communication resources that allow to track individual's course-grain geo-tagged activity unobtrusively.

Table 2. Selected studies leveraging wearable accelerometers to monitor PD movements

Contribution group	Sensor type and placement	Intervention Interest	Setting (task)	Accuracy results
Bonato [12]	ACC(8): two on each arm; one on each thigh; right shin and sternum + 8 EMG's	"OFF" state, "ON" state, dyskinesias	Lab	3 clusters of data corresponding to "ON", "OFF" and dyskinesias
Keijsers [13]	ACC(6): both upper arms, both upper legs, wrist at most affected side, and sternum.	Dyskinesias	Lab simulated home environment	> 93% accurate in whether or not dyskinesia present
Keijsers [9]		"OFF" state "ON" state		58-97% sensitivity, 70-97% specificity for detecting ON/OFF
Moore [10]	Combined ACC+gyro(1): worn just above ankle	Stride length	Lab/home	100% agreement between Stride length and video observation
Moore [11]		Freezing of gait	Lab	78% -89% of freezes detected
Bächlin [15]	ACC (3): above ankle, above knee, waist	Freezing of gait	Lab	73.1% sensitivity 81.6% specificity
Patel [16]	ACC (8): 2 per limb	Selected tasks from UPDRS	Lab (UPDRS)	2.2-3.4% error in UPDRS score
Patel [17]			Lab (UPDRS)	Within 0.5 points on UPDRS scale of 0-4.
Zabaleta[18]	Combined ACC+gyro(6): 3 on each leg	Freezing of Gait	Lab	51.1-82.7% of freezing episodes correctly detected
Weiss[19]	ACC (1): on waist	Gait Variability	Lab & home	Gait variability was larger in PD
Griffiths[20]	ACC (1): on wrist of most affected side	Bradykinesia, Dyskinesia	Lab	Modest agreement with UPDRS
Tsipouras [7]	6 sets of ACC+gyro: one on each limb+waist	Dyskinesia	Lab	~84% Accuracy
Mera[22]	ACC+gyro (1): on finger	Bradykinesia & tremor	Home (UPDRS)	Medication response detected
Zwartjes[23]	Combined ACC+ gyro(4): trunk, wrist, thigh and foot of most affected side	Tremor, bradykinesia, hypokinesia	Lab (UPDRS) tasks and daily tasks	Overall 98.9% accuracy
Das[11] 2 PD patients	ACC (5): wrists, ankles, waist	Subject specific motor signs	Regular daily activities	>90% accuracy

Fig. 1. Smartphone with built-in sensors and body sensor network device & Smartwatch with accelerometer

In the SPARK framework we exploit both a smartphone and a smartwatch to establish an mobile health (mHealth) system for active and passive monitoring of PD patients. Active monitoring is offered by a mobile Parkinson disease rating scale (mPDRS) designed by our research group. Passive monitoring is performed by collecting accelerometer data from a Pebble watch worn on the affected limb. In Section 4, we describe role of SPARK's elements including their functionality and applicability.

3.2 mPDRS: Mobile PDRS for Personalized PD Interventions

Most investigations of monitoring movements in PD utilize wearable sensors. Other aspects of PD symptoms such as facial expression, speech quality and components of ADL (listed in Table 1) are overlooked in monitoring PD progression, although they hold great clinical significance in improving treatment and life quality of PD patients [23, 24]. Harnessing the power of SPARK framework, we have built a mobile version of UPDRS – the mPDRS (mobile PDRS) – to objectively monitor PD severity in remote as well as clinical settings. In other words, mPDRS is an effort to conduct a subset of UPDRS tests through the Pebble watch and smartphone. The subset of tests is selected in the way that multidimensional symptoms manifested in various forms such as motor movements, speech, facial tremors, gaiting functions, and disabilities in performing ADL are considered to offer clinicians varieties of clinical data for improving treatment outcomes.

4 SPARK Framework

The overarching goal of SPARK framework is to monitor clinically relevant multidimensional data – such as facial tremors, dysfunctional speech, periods of dyskinesia, and instances of freezing of gait – from smartphones and smartwatches that are carried by the patients remotely. As shown in Figure 1 and Figure 2, SPARK is three-layered framework, enabling collection of sensor data from a synergistically functional system consisted of a smartphone and a smartwatch. Each layer in SPARK is designed such that physicians can define personalized interventions for each PD patient.

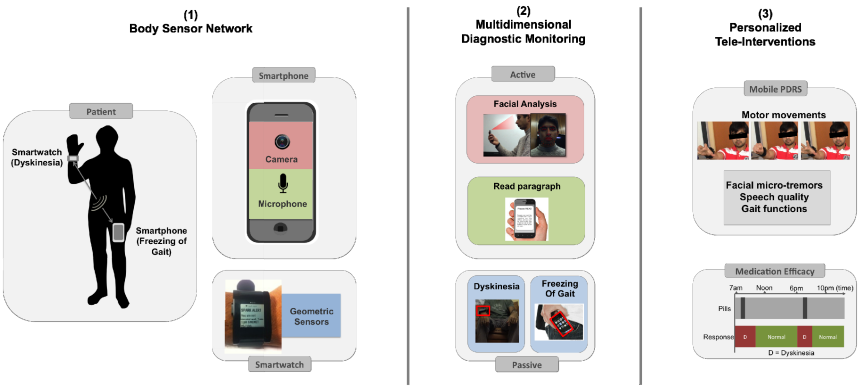

Fig. 2. Three-layered Framework of SPARK for personalized PD interventions

4.1 Body Sensor Network (Layer 1)

Body sensor network (BSN), also referred to as wireless body area network (WLAN), is a collection of wearable computing and sensing devices, communicating with one another to provide contextual awareness to end-users in various application domains. In SPARK, BSN consists of a smartphone and a smartwatch as a network of sensing devices. A smartwatch worn on the patient's wrist records accelerometer data that are streamed to smartphone.

Smartphone-Smartwatch Communication. We used the Pebble watch data logging API [25], enabling the data transfer from Pebble to smartphone. Pebble can create multiple time-stamped logs that are queued and then transferred at set intervals when a Bluetooth connection with smartphone is available. In order to reduce energy consumption and battery usage, Pebble batches up data and sends it over to the smartphone periodically.

Clinically-smart Data Management Layer. We aim to design a clinically-smart data management layer (CsDML) that segregates clinically relevant data from background noise on smartphones and makes the system more efficient in terms of energy and data transmission. The targeted CsDML is based upon on-line learning algorithms that incorporate event-driven adaptive sensor sampling and also allow forming context-awareness personalized to individual needs.

4.2 Multidimensional Diagnostic Monitoring (Layer 2)

This second layer of SPARK comprises data storage, analysis, and visualization layers implemented in a private SPARK cloud. The SPARK cloud stores data from subjects and runs machine learning algorithms to classify the symptom severity. In this layer, machine learning algorithms are aimed at looking at features of PD symptoms in the following ways:

1. Facial tremors**:** UPDRS test no. 19 involves physicians to score facial tremors through visual observation. In this part of SPARK technology, we attempt to automate this process through smartphone. PD patients are prompted to watch a short slideshow on their smartphones. While they watch the slideshow, the front camera of the smartphone records their facial video. The recorded face videos are then uploaded to the SPARK cloud for further clinical analysis. We have developed computer vision algorithms [27] to clinically score facial tremors in the recorded videos.
2. Speech quality**:** UPDRS test no. 18 asks PD patients to read a short paragraph and hence, physicians can score their speech functions. Similarly, SPARK adopts this step by allowing patients to read a paragraph displayed on their smartphone screens while the built-in microphone of the smartphone records their voice.
3. Motor tremors: There are many UPDRS tests that require physicians to score motor tremors of PD patients when they pay in-clinic visits. SPARK offers to collect patient's motor data through active or passive monitoring. In order to personalize PD monitoring and treatment, SPARK facilitates physicians to place the Pebble smartwatch on most affected limbs of their patients.

4.3 Personalized Interventions

SPARK will provide recommendations to physicians for medication changes. As shown in Figure 3, we will use an individualized conditioned hidden Markov model for predicting ON (when movement is good and medication is working) and OFF states (when movement is bad and medication is not working). Predicted OFF states will be used to recommend medication adjustments.

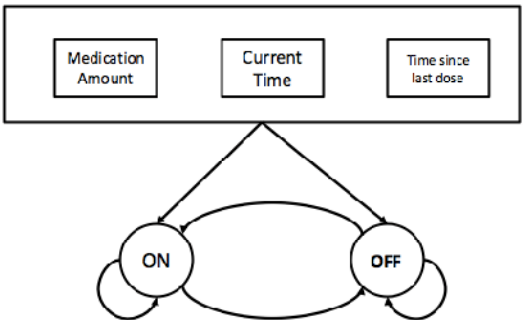

Fig. 3. Conditioned Hidden Markov Model for predicting ON/OFF states to generate recommendations for medication changes and minimizing OFF. Additional factors may be added.

5 Pilot Trials with the SPARK Framework

We conducted focus group studies on 5 control subjects. The studies were performed in laboratory settings to collect the experimental data through the SPARK framework. In the studies, we collected multidimensional data of subjects using the smartphone/smartwatch framework.

5.1 Facial Tremors

A cardinal feature of PD is diminished facial expression ("masked facies") and therefore, it is crucial for physicians to look at the pattern of masked facies of their patients when they are remotely located. We have designed a smartphone app – FaceEngage [27] that uses the front facing camera to record facial videos while the participant watches a 2-min slideshow of emotionally neutral images (Figure 4). We have also developed computer vision techniques to process face videos to detect attributes of interest such as blinking rate and parted lips instances which serve as good indicators for scoring masked facies [27].

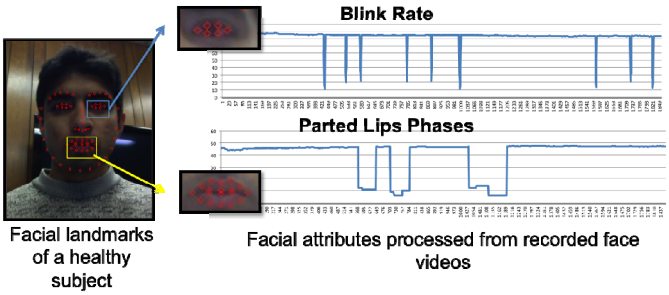

Fig. 4. Facial analysis of healthy individuals with emphasis on monitoring facial attributes associated with PD

5.2 Speech Analysis

Speech impairments have been associated with PD, and voice deteriorates with PD progression. Speech signals are an ideal choice for the remote monitoring of the Parkinson symptoms because they are easy to obtain, there is no special skill or instrumentation required, and they are noninvasive in nature. In the SPARK framework we propose to use active and passive speech monitoring of PD patients and use features of speech impairment – such as reading duration, pitch, jitter and shimmer – to monitor the progression of PD.

5.3 Active Monitoring of Movements

In active monitoring PD patients will be asked to perform the motor movements described in the mPDRS scale. These motor movements include wearing the smartwatch on a limb. Typical movements in mPDRS include finger tapping, opening and closing of hand, finger pointing, pronation and supination, foot tapping, walking, and getting up from a seat while hands crossed. Figure 5 shows the typical profile of a 3 axis accelerometer data from a subject performing the mPDRS scale. It is clear from the figure that each maneuver in the mPDRS carries a specific signature easily identifiable in raw accelerometer data.

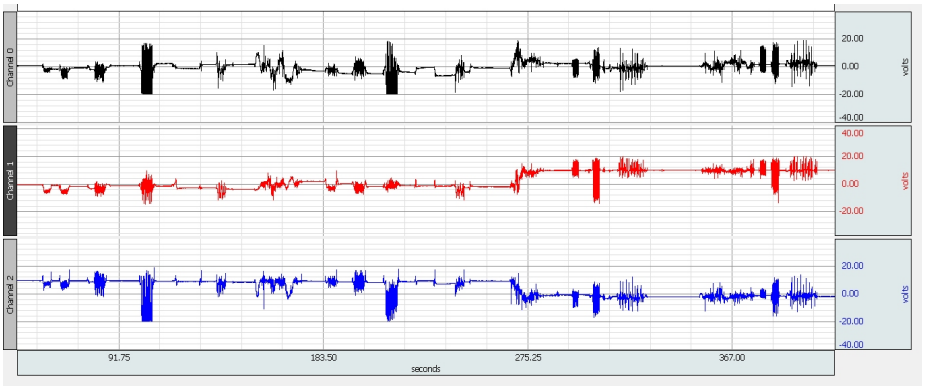

Fig. 5. 20 movements captured on accelerometers of the smartphone while a participant strapped the smartphone sequentially on wrists and then ankles (one location at a time) during mUPDRS trials

6 Conclusions and Future Work

We have presented a novel framework for personalizing the management of PD. SPARK uses smartphones and smartwatches to track symptom severity in real world situations and assess how medications affect symptoms. SPARK provides ways to measure speech and facial expressions/features, which are crucial for the understanding of PD severity. We are pilot-testing the current framework with the PD patients and evaluating the usefulness of this framework for all the stakeholders (patients, clinicians, caregivers, and family members).

While the SPARK framework is encouraging, there are inherent limitations of the usefulness of SPARK in PD interventions. Our project is focused solely on the motor features of PD and does not incorporate medication side effects or non-motor features (e.g., psychiatric disturbances, sleep problems, autonomic dysfunction, cognitive issues). We plan to incorporate non-motor features and side effects into personalized predictive models in the future. Despite our effort to maximize compatibility, there will be PD patients that will not be able to use SPARK due to their inability to adopt new technologies such as smartphones. Further, sensor misplacement, patient log errors, device malfunction, loss of data, and limitations of algorithms are challenges we may encounter.

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