mHealth Technologies Towards Parkinson's Disease Detection and Monitoring in Daily Life: A Comprehensive Review

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(Methodological Review)

***Abstract*—Parkinson's disease (PD) can gradually affect people's lives thus attracting tremendous attention. Early PD detection and treatment can help control the disease progress, relief from the symptoms and improve the patients' life quality. However, the current practice of PD diagnosis is conducted in a clinical setup and administrated by a PD specialist due to the early signs of PD are not noticeable in daily life. According to the report of CDC/NIH, the diagnosed time of PD ranges from 2-10 years after onset. Therefore, a more accessible PD diagnosis approach is urgently demanded. In recent years, mobile health (for short mHealth) technology has been intensively investigated for preventive medicine, particularly in chronic disease management. Notably, many types of research have explored the possibility of using mobile and wearable personal devices to detect the symptom of PD and shown promising results. It provides opportunities for transforming early PD detection from clinical to daily life. This survey paper attempts to conduct a comprehensive review of mHealth technologies for PD detection from 2000 to 2019, and compares their pros and cons in practical applications and provides insights to close the performance gap between state-of-the-art clinical approaches and mHealth technologies.**

***Index Terms*—Mobile computing, public healthcare, body sensor networks.**

I. Introduction

PARKINSON'S disease (PD) is a disorder of the central nervous system which broadly affects 6.9 million people in 2015 and estimates to influence 14.2 million people by 2040 in the world [1]. Although PD cannot be completely cured, PD patients benefit from early detection and treatment. They not only help relieve symptoms [2] but extend their lifespans [3]. However, early detection of PD is usually difficult. The reason is that PD is a progressive disease where the symptoms grow gradually but are not obvious at the early stage. One solution is to get an entire evaluation with the help of a neurologist or a PD specialist periodically. Unfortunately, even in a wealthy country like the US and Europe, more than 40% of individuals older than 65 have no chances to meet a neurologist or PD specialist, not to mention people living in other developing country [1]. Consequently, an accessible approach for early PD detection is required but still under-explored.

Fortunately, the pervasiveness of mobile devices (*e.g.*, smartphone, and smartwatch) and the emergence of mobile health (for short mHealth) technologies are addressing this problem. The characteristics brought by mHealth technologies are three folds. First, mHealth brings innovative sensing modality. Traditionally, PD detection is conducted in a clinical or lab-based environment supervised by neuroscientists and specialists. Although these approaches work well, the cost of enormous human labor and large devices makes them inaccessible in daily life. Instead, a mobile solution is more feasible for daily use as a smartphone nowadays is no longer a communication tool but a smart device embedded with multiple sensors. These built-in sensors (*e.g.*, camera, microphone, and accelerometer) can provide access to predict the risk of PD even in a non-clinical environment.

Second, advanced computer-assisted techniques assist existing approaches to provide accurate PD detection. Although a set of clinical approaches can provide accurate PD detection, most of them are inaccessible in daily life. Without specialized training, humans can misdiagnose PD. For example, Ali, as one of the most famous examples of PD, took four years to diagnose [4], thus miss the best time for treatment. The emergence of machine learning and data mining is compensating for this defect. Rather than only relying on human experience, these computer-assisted approaches utilize multiple features simultaneously, thereby making an accurate PD risk prediction promising.

Third, mHealth brings an opportunity for continuous monitoring. As a chronic disease, PD progresses slowly, and its

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symptoms are not visible in the early stage. To detect PD biomarkers in the early time, it requires an approach to monitor the health condition continuously and remind a user of the occurrence of PD biomarkers. Traditional clinical approaches cannot achieve this goal. However, mHealth provides it the opportunity that mobile devices (*e.g.,* smartphone) can provide continuous interaction and monitoring to detect PD biomarkers in daily life. All these advantages make early PD detection promising.

In this paper, we give an overview of PD detection using mHealth technologies and their current challenges. We discuss a series of cutting-edge work that emerged in the past twenty years. For each work, we first pay attention to its sensing modality and symptom genre. Then, we explore their performance and implications. Finally, we discuss the challenges and opportunities they have ever met.

The goal of this review is first to bring the novice not working in this field quickly up to date with where things stand. Second, we will help either experienced or non-experienced researchers to understand the existing challenges and opportunities. Last but not least, we hope our work to be not only an updated collection of the most relevant existing work but stimulates research in this area.

The rest of this paper is organized as follows: we discuss the existing work and our paper selection criteria in Section II. We introduce the background, including PD rationale and PD detection with mobile devices in Section III. Then, we study detection of motor symptoms and non-motor symptoms in Section IV and Section V, respectively. Afterward, we investigate multi-domain PD detection in Section VI. On this basis, we identify the research issues and challenges in Section VII, and propose the research opportunities in Section VIII. Finally, the work is summarized in Section IX.

II. Existing Work and Paper Selection Criteria

There is no present paper comprehensively survey the employment of mHealth on PD detection. Some researchers only focused on motor symptoms detection. For example, Lieber *et al.* [5] studied how can accelerometer helps PD detection in both the clinical setting and daily life. Pasluosta *et al.* [6] surveyed the effect of wearable computing on PD detection. Printy *et al.* [7] mainly explored the feasibility of using the smartphone-based application to detect the motor symptoms. These researchers did not pay attention to the significance of non-motor symptoms. Instead, our objective is to provide a comprehensive review of both motor and non-motor symptoms in PD. Some scholars [8] studied the mobile phone application in PD. Instead, our study will focus on technology in both smartphones and wearable sensors.

Some scholars pay attention to the impact of the machine learning technique on PD detection. For example, Pan *et al.* [9] compared two techniques in terms of accuracy in classifying tremors for PD. Bind *et al.* [10] [11] studied the performance of different machine learning techniques on PD detection and concluded the best one based on best accuracy values. Belic *et al.* [12] reviewed applications of artificial intelligence in PD detection. Instead, our objective is to provide a comprehensive

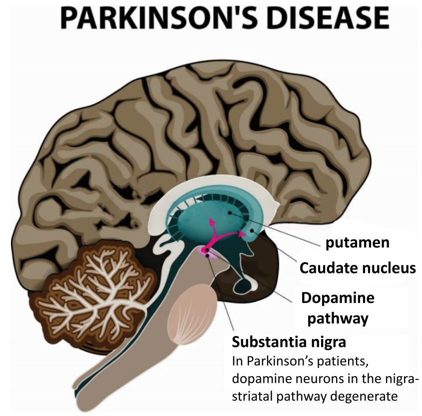

Fig. 1. The death of cells in the substantia nigra era destroys the dopamine pathway thereby results in insufficient dopamine in these areas.

review to understand how mHealth helps early detection of PD in daily life. The focus will be the symptoms genre and sensing modality, as well as the classification model and performance. More importantly, we care about the limitations and challenges and discuss potential solutions.

We survey papers published in the last twenty years, within an online digital library, including IEEE, PubMed, Science Direct, and ACM, with a focus on PD detection and mHealth. The search encompassed papers dealing with PD symptoms genre, sensing modality, and classification model design. We select 10 papers dealing with gait and balance impairment, 14 papers dealing with tremor and finger-related movement, 7 papers dealing with vocal impairment, and 12 papers dealing with other symptoms. We also include 4 system papers that investigate the multi-view PD detection, PD severity estimation, and PD medication adherence management. For each topic, papers are arranged in chronological order. First, we briefly introduce the background. Afterward, we discuss the first work in the area and explore its extension. We finally conclude and express our views.

III. Background

A. PD Rationale and Impact

As a progressive central nervous disorder, the progress of Parkinson's disease (PD) can be described as follows. To begin with, the deaths of cells happen in the substantia nigra due to unclear factors. Then, it destroys the dopamine pathway and results in insufficient dopamine in these areas (Fig. 1). PD mainly affects motor ability. In the early stage, the most apparent motor symptoms can include but not limit to bradykinesia (slowness of movement), tremor, and postural instability. These symptoms can progressively make patients lose their mobility over time. PD can also induce some non-motor symptoms. For example, mood disorders, such as anxiety and depression, are primary symptoms, and more than a third of PD patients experience with mood disorders in their early stages. Organs disorders, including vocal impairment, stomachic dysfunction, and diminished smell, can as well occur in a very early stage.

Although recent advances of technology such as neuroimaging and gene detection have allowed for precise pinpointing of own tissue and genes associated with the tremors and freezes of body parts and extremities, they suffer from the limitation of time and resource cost. Nowadays, only hospitals or specific research labs can provide a precise diagnosis. Due to such inaccessibility, people usually will not pursue an overall examination until the symptoms are obvious, by which more than 70% nerve cells are permanently impaired. Accordingly, early PD detection is still challenging.

B. PD Detection With Mobile Devices

The emergence of mHealth technologies is helping early PD detection. The usage of mobile devices has been rapidly increasing worldwide. At the end of 2018, 77% [13] of the population in the U.S. own a smartphone, and this number is projected to increase by about 4 percent every year. Since the smartphone holds advantages such as affordability, portability, and reliability, it was recently considered as an excellent choice to help early PD detection in daily life.

The benefits of mHealth technologies are two folds. First, mHealth brings a novel sensing modality for detecting PD biomarkers. Different from some traditional clinical-based or lab-based methods where people are required to wear types of sensors to perform types of experiments in a controlled environment, a smartphone with multiple embedded sensors (*e.g.*, accelerometer, gyroscope, camera, and microphone) enables PD detection in daily life. Even more, a smartphone can provide the ability of long-term monitoring, whereas the clinical method is helpless. For example, the built-in gyroscope and accelerometer can continuously track the motor fluctuation of a user during his housework. The built-in microphone can continuously monitor a user's sleep condition.

Second, mHealth brings computer-assisted techniques for helping analyze PD symptoms. Traditional diagnosis relies on the longitude experience from a physician and the self-reporting table (*e.g.*, UPDRS). Physicians, without specialized training, easily misdiagnose PD as other diseases. On the contrary, computer-assisted approaches, for example, machine learning, nowadays can well assist PD detection through learning sufficient existing cases.

IV. Detection of Motor Symptoms

In the past twenty years, PD motor symptoms are most recognizable and attract tremendous attention from researchers. To better follow the research progress, understand the challenges researchers have met, and, more importantly, acquire insights from their work, we classify existing works into two major categories, active sensing, and passive sensing. In particular, an active-sensing system still requires a user to carry out some experiments for detecting PD biomarkers. In contrast, a passive-sensing system allows detecting PD biomarkers from a user's daily-life activities without performing any specific test (*e.g.*, balance test, speech test, and handwriting test).

In this section, we mainly focus on active sensing. More specifically, we are going to cover four types of motor symptoms. They are freezing of gait (FOG), slowed movement, affected handwriting, and impaired balance. For each PD symptom, we first provide its background and then unfold its related works. These works are all highly relevant to mHealth. We arrange these works in a timeline so that readers can clearly understand the research progress in recent years.

A. Impaired Gait and Balance

Approaches with Wearable Sensors: PD is responsible for affecting cognitive control of the body, which includes, but not limits to, kinematic impairment. Based on this background, motor learning becomes a benchmark in the domain of PD detection. Of all the studies, FOG is one of the most disabling symptoms, which is widely studied, and the detection of FOG is widely adopted in a clinical assessment. Traditional assessment of FOG relies on a subjective measurement from the physicians or the self-reporting from patients. These clinical approaches usually relied on the experience in the past, resulting in insufficient accuracy. To address this problem, a series of works were proposed to coordinate with the clinical approaches by utilizing some inertial sensors. Moore and his group adopted wearable sensors to perform FOG detection in 2008 [14]. Afterward, a series of incremental work was proposed to increase the accuracy, reduce the size of the sensors, and minimize power consumption.

Mazilu *et al.* [15] studied the FOG detection with a smartphone-based system. Rather than utilizing the built-in inertial sensors, the smartphone was adopted as a computing unit, and the external sensors performed FOG measurement. Wang *et al.* [16] published an extension in which the smartphone was also viewed as the computing unit, and FOG measurement was achieved by an accelerometer, which was placed on the back of every patient. To track the daily-life variation of the symptoms, the authors also developed an application on the smartphone. Through this way, patients can understand physical conditions with smartphones.

One rising question is why those mentioned works viewed a smartphone as a computing unit rather than a sensor. People might no more need any external hardware if the built-in sensors of a smartphone can also achieve data collection. This is because the researchers believed the accuracy of FOG detection is sensitive to the placement of sensors. They usually put the sensors in the ankle or at the back where they thought that they can reveal the motor impairment better. It is hard and inconvenient to put a smartphone in the ankle.

Other scholars challenged its correctness. Pepa *et al.* [17] studied employing the built-in sensors of a smartphone to detect FOG by placing the smartphone at the subjects' hip. Kim *et al.* [18] published a significant extension which performed the comparative analysis to understand the impact of different positions of sensors on detection accuracy. In their experiments, the authors separately placed a smartphone on the chest, waist, pocket, and ankle of a subject to collect gait information. They achieved a sensitivity of 86% when putting the smartphone at the waist, and they can still achieve a sensitivity of 84% when putting a smartphone in the trouser pocket. The results showed

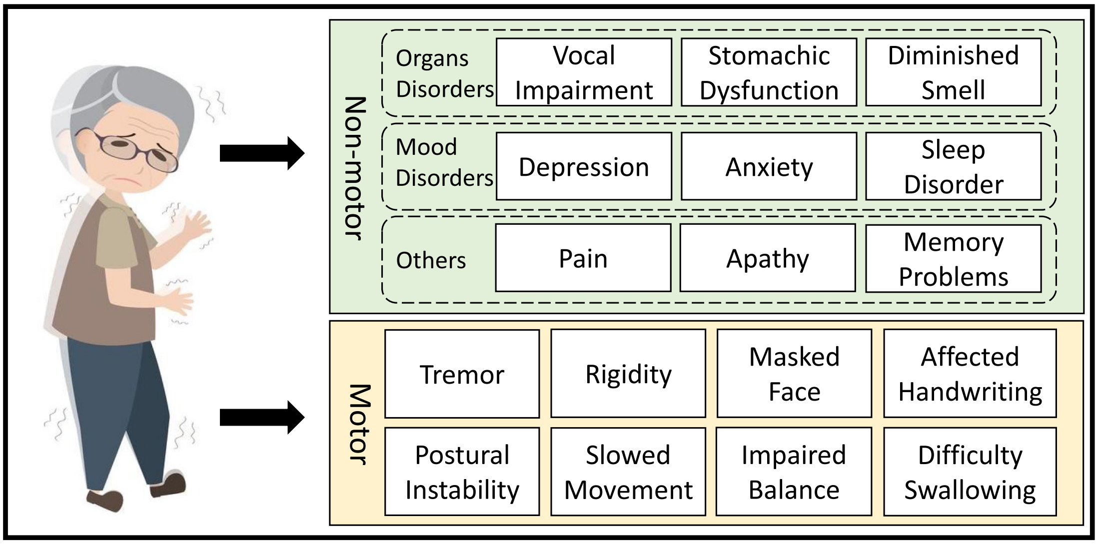

Fig. 2. An overview of the PD symptoms including the motor symptoms and non-motor symptoms.

that putting a smartphone in the pocket for FOG detection is also feasible. More importantly, their results indicated that users can replace wearable inertial sensors with smartphones to achieve more user-compliance PD detection.

Gait analysis via wearable sensors is one of the most promising ways to achieve passive PD detection. Din *et al.* [19] tried to analyze gait activities in a free-living condition. 47 PD patients and 50 healthy people participated in this 7-day long study. Each subject was asked to wear an accelerometer-based sensor on the low back. To facilitate a study on control group, the measurements were acquired under the clinical environment by the same group of people. The results showed that some gait features presented very similar in a clinical environment for both PD patients and healthy people, but were significantly different when measurement took place in free-living conditions. This conclusion indicated that measurement in free-living conditions can more accurately reflect mobility performance than measurement in a clinic. This encouraging result also showed the potential of passive sensing to track and detect the PD symptoms in daily life.

On this basis, Cheng *et al.* [20] published an extension, which explored the possibility of gait analysis using a smartphone in a free-living condition. The authors enrolled 44 PD patients and 35 healthy people and took a 24 week-long experiment. More than 30,000 hours of data were collected passively. Results showed that PD patients and healthy people can present a significant difference in movements, such as turning angle, turning speed, step frequency, and per-step power. Compared with the wearable sensor, the authors also claimed that smartphone achieved a higher acceptance and adherence rate in daily-life usage.

Approaches with Computer Vision: The development of artificial intelligence and information engineering is helping CV technologies become flexible nowadays. A sensor-free system was developed by Takac *et al.* [21] to achieve ubiquitous monitoring for gait analysis. Compared with previous work, the subjects were not required to wear a mark, and there were no strict requirements for the placement of the camera. Besides, the authors combined both sensor-based with image-based technologies in their work, which can be described as follows. In a smartphone, the embedded sensors such as gyroscope and 3-axial accelerometer achieved FOG detection, and the image-based system provided spatial information such as position, orientation, and pose of the subject.

Afterward, a smartphone-based FOG State Interpreter (FSI) module computes a high-level probabilistic integration of the gait detection model and spatial context to provide a concluding estimation. One disadvantage of their work is the restriction in hardware. In order to accurately obtain the skeleton information for pose estimation, they employed the Kinect, a type of camera, to obtain depth information. The depth camera restricted the generalizability of their system and should be taken into consideration in further study.

Fortunately, up-to-date technologies can achieve skeleton extraction with a 2-D camera. OpenPose [22] implemented a real-time system which obtains the skeleton information through only a single image indicating that an ordinary camera is enough for data collection. Based on this basis, Ajay *et al.* [23] developed a sensor-free system to perform PD detection with these skeleton information. Data came from youtube, which was either recorded by webcam and smartphone, and they achieved a predicting accuracy of 93.75%. This work further decreases the dependence on hardware and proves that it is available to come up with a test-free and sensor-free solution to achieve pervasive PD detection. Their work also indicates that publicly available videos will have the potential to provide the ability of disease screening in the future.

B. Impaired Movement

Impaired movement is an essential branch when evaluating the motor-related symptoms. Dhamala *et al.* [26] studied the correlation between PD and rhythmic finger motion with the help of magnetic resonance imaging (MRI). Based on this basis, Wurster *et al.* [27] further studied the neural correlates of frequency-related finger movements. They designed and implemented a finger-tapping test on a smartphone. The tapping test contains three different kinds of frequencies (*i.e.* 1Hz, 2Hz, and 4Hz), and it monitored the brain-behavior of patients according to different tapping speed. There are two conclusions. First, PD patients can only achieve the same tapping response rates as well as healthy people when the frequency of the task is set to 1Hz. Second, the MRI result showed that the correlation between inverse neural activity and frequency response is strong in healthy subjects, from which the authors can observe a very high Blood-oxygen-level-dependent (BOLD) signal. However, the authors observed that this correlation was not obvious in PD patients this theoretical basis provided by this paper promoted further study.

To better understand the correlation between leap motion and PD, researchers study sensor technology as well as the classification model to improve the performance of PD detection in recent years. For example, Butt *et al.* [28] employed the Microsoft Kinect sensor to capture motion information of patients. Eskofier *et al.* [29] developed a wearable sensor system to collect postural movements. The authors also studied different classification models to analyze the collected data, and they found out that CNN can achieve the best accuracy of 90.9%.

Smartphones today offer a range of capabilities, such as communication and processing, facilitating them to become personalized and even ubiquitous gateways to health information anytime, anywhere. In this context, smartphones are adopted in motion evaluation recently. Bermeo *et al.* [30] developed a smartphone-based system to monitor tremors. The authors used a wearable sensor to collect data. Afterward, data is transmitted to a smartphone through a wireless signal. The smartphone is then responsible for data analysis and management. Printy *et al.* [7] implemented a finger-tapping test in a smartphone. They developed a smartphone APP called Bradyapp, which contains four kinematic tasks, such as repetitive tapping and alternating tapping. Experiments with 26 subjects were conducted to study the performance, and the authors achieved the best accuracy of 94.5% with an SVM classifier. An extension was published by Figueras *et al.* [31], who implemented the finger-tapping test in an Android platform. One contribution is that they utilized the built-in sensors rather than the external hardware to achieve PD detection with high user adherence.

C. Affected Handwriting

In recent years, researchers have started to evaluate types of motor activities to understand how behaviors will be affected due to PD. However, one common disadvantage of these tasks is that they are too complicated to be generalized for daily-life usage. For example, both tapping test and balance test require users to follow specific instructions. Although these tests achieve high detecting accuracy, they achieve low user adherence. Consequently, rather than designing some complicated tasks to predict the PD severity, researchers try to find out an efficient solution that can reveal PD risk from daily-life behaviors. Under this background, evaluation of handwriting changes comes forth as a diagnostic tool.

Teulings and the team [32] published the study of affected handwriting. They discovered and surveyed several parameters correlating handwriting impairment with PD, which can conclude as follows. 1). PD patients may have smaller handwriting size or fail to keep their stroke size constant as handwriting progresses. 2). The force amplitude required to produce and maintain large keystroke sizes may not be present in individuals with PD. 3). PD individuals will need relatively more time than average for producing writing strokes. 4). PD individuals are highly reliant on visual feedback. Teulings identified features based on the points above and the time since other studies have researched using computational prowess to enhance PD diagnostics within society.

Alongside Teulings' work, newer and better features are identified, appropriate to PD detection. For example, Nogueras *et al.* [33] concluded that biometric potentials between on-surface writing movements and in-air hand trajectory movements are different. Accordingly, measuring two of the components are non-redundant. Based on this, Drotar *et al.* [34] took handwriting analysis from both a perspective of surface writing and a perspective that examines hand movements when writing happens in the air. They adopted SVM as the classification model and achieved an accuracy of 80%. An extended work [35] was followed to identify critical markers of handwriting and achieved an accuracy of 88% with almost equal sensitivity and specificity.

Deep learning as a new-generation machine learning technique is helping PD detection achieve high accuracy. One of the most recent works was published by Periera *et al.* [24], who first proposed a system that utilized CNN as a classification model into PD detection with handwriting data. The insight behind is that the performance of traditional machine learning relies on features selection, and improper features can undermine the performance. Consequently, the authors replaced traditional classifiers with CNN, in which the convolutional layers can automatically learn the features, and fully-connection layers can achieve PD detection. Another novelty is the authors developed a smartpen, which contains a microphone, an accelerometer, a grip pressure sensor, and a refill pressure sensor in order to collect handwriting data from multiple views. 224 PD patients and 84 healthy people participated in this study, during which each testee was required to finish a writing exam with the smartpen. The authors achieved the best accuracy of 92.2%, which indicated that handwriting data can provide useful information to reveal PD symptoms in daily life.

The development of a multi-touch screen enables a smartphone to sense some finger activities, such as writing, flicking, and drawing. Under this background, Aghanavesi *et al.* [25] implemented a handwriting task on the smartphone. They developed an Android application containing a spiral drawing test, which asked every testee to trace a pre-drawn Archimedes spiral as fast and accurately as possible. Aghanavesi *et al.* [36] published an extension, in which they added a tapping test and employed data from both two tests to jointly evaluate PD severity.

TABLE I
OVERVIEW OF THE SELECTED PAPERS WORKING ON MOTOR SYMPTOMS DETECTION VIA SMARTPHONES. THE CLASSIFICATION PROBLEM IS PD/HEALTH CLASSIFICATION

Authors	Sensing Modality	Symptoms	# of Subjects	Methodology	Performance
Pepa *et al.* [17]	Smartphone	Impaired Gait	18 PD	Feature Extraction	Sens. 82.34%
Printy *et al.* [7]	Smartphone	Impaired Tapping	26 PD	SVM	Accuracy 94.5%
Periera *et al.* [24]	Smart Pen	Affected Handwritting	224 PD and 84 CTL	CNN	Accuracy 92.2%
Aghanavesi *et al.* [25]	Smartphone	Affected Handwritting	19 PD and 22 CTL	NA	NA
Din *et al.* [19]	Wearable Sensor	Impaired Gait	47 PD and 50 CTL	Feature Analysis	NA
Cheng *et al.*. [20]	Smartphone	Impaired Gait	44 PD and 35 CTL	Feature Analysis	NA
Ajay *et al.* [23]	Webcam	Impaired Gait	10 PD	OpenPose [22]	Accuracy 93.75%

Naseer *et al.* [37] published an extension, in which they adopted deep transfer learning to achieve higher accuracy of PD detection. They first adopted the pre-training model from ImageNet and PaHaW dataset. They then used the fine-tuning-based approach to retrain the existing model on their handwriting dataset. They achieved an accuracy of 98.3%, which revealed that their transfer learning-based approach achieves better accuracy of PD detection when compared with existing state-of-the-art work.

D. Summary

We highlight the cutting-edge works (see Table I). We observe that there exists a clear storyline, during which researchers employ mobile devices to achieve early detection of PD. On the one hand, researchers have tried to simplify the procedure of PD detection. They employ wearable sensors to assist the PD detection, which usually relied on human experience in the past. In the process, wearable inertial sensors are adopted, but smartphones progressively replace them due to the stronger computing ability, convenience, and pervasiveness. Also, the incremental understanding of PD and the evolution of the classification model are making PD detection promising. On the other hand, researchers have noticed the importance of user adherence in PD detection. In order to achieve high user adherence, they study protocols of passive sensing by merging the progress of PD detection into users' daily routine. To understand the difference between active sensing and passive sensing, researchers measure the performance gap, and the encouraging results suggest that the mobile system shows the potential to facilitate PD detection in daily life.

V. DETECTION OF NON-MOTOR SYMPTOMS

With the developing understanding of PD, the detection and treatment of non-motor symptoms, which are considered as the early signs, are increasingly emphasized. However, little attention is focused on this domain. One of the most important reasons is that the sensors are usually hard to directly measure the conditions of these non-motor symptoms, such as apathy, pain, depression, and anxiety.

In this section, we will first study the detection of vocal impairment, which is considered as a pre-motor symptom of PD. Afterward, we present some cutting-edge researches in which the authors successfully recognize non-motor vital signs through a mobile device.

A. Vocal Impairment

Since vocal impairment has been proved one of the pre-motor symptoms which emerge at the very early stages [42], researchers have laid great emphasis on vocal impairment detection to facilitate PD detection.

Considering the cost and inconvenience of the regular physical visit, Little *et al.* [38] proposed a cutting-edge solution to study the suitability of vocal impairment analysis via a telemonitoring system. Different from the traditional clinical-based analysis where environmental factors are strictly controlled, the telemonitoring system needs to deal with the dynamic environment which has highly variable acoustic sources. To achieve this, the authors particularly explored the pitch period entropy (PPE), which is a robust feature sensitive to observed changes corresponding to PD. 31 subjects participated in this research and contributed 195 samples in total. They employed SVM as a classification model and achieved an accuracy of 91.4%. In general, this work is the very first one that proves the feasibility of detecting PD in daily-life scenarios.

As a preliminary work, Little *et al.* [38] only verified the possibility of PD detection via one type of voice (i.e., the sustained vowels). On this basis, Sakar *et al.* [39] studied how PD can influence the generation of different types of voice. They collected four types of audio data, i.e., words, number, short sentence, and the sustained vowels, from 20 PD patients and 20 healthy people. For each category of audio data, the authors extracted 26 features and utilized KNN and SVM as the classification model, respectively. The results showed that sustained vowels are the most significant PD-discriminative signatures when compared to the other types of voice. Also, sustained vowel "o" presents better performance than other types of sustained vowels.

Later, Jeancolas *et al.* [40] published extensive work to continually evaluate the audio data with four tasks, which are sustained vowel pronunciations, fast syllable repetitions, free speech, and reading. Different from previous works that achieved PD detection through acoustic analysis with global features, the authors employed Mel-Frequency Cepstral Coefficients (MFCC) as a type of short-term features combined with Gaussian Mixture Models (GMM) as the classification model. They collected 1110 samples from 74 subjects and the reading task achieved the best performance with an accuracy of 91.4%.

With the incremental development of machine learning, deep learning-based solution is progressively employed in the mobile health system to achieve high performance. DeepVoice [41] first adopted Convolutional Neural Network (CNN) into PD detection with audio data. The authors designed and implemented a smartphone-based application that contained three parts, audio data collection, spectrogram representation, and PD prediction. At the smartphone end, the users were asked to perform a 10-second long sustained vowel test. At the server end, the spectrogram was adopted to represent the audio data into both the time and frequency domain, and AlexNet was selected as the classification model. Besides performance, the authors studied the relationship between the length of audio data and the performance of PD detection. Results showed that the accuracy of PD detection increases obviously when the data length increases from 1 second to 5 seconds but progressively gets saturated if data is longer than 5 seconds.

On this basis, Alavijeh *et al.* published an extention [43], who proposed a new approach to identify the segments of the audio data which violate the test protocol with high accuracy. The audio data is first to split into variable duration segments to fit an infinite hidden Markov model (iHMM). They adopted a multinomial naive Bayes classifier and achieved an accuracy of 96%.

B. Other Non-Motor Symptoms

The pervasiveness of IoT devices enables continuous access to vital human signs in daily life. As a result, vital signs monitoring through a mobile system has attracted great attention. The applications include but not limit to following items: a) heartbeat rate detection [44]; b) breathing rate detection [45]; c) blood pressure detection [46]; d) blood oxygen level detection [47]; e) blood glucose level detection [48]. These add-on sensors for measurement are usually connected to a smartphone through physical wiring or via wireless connections (*e.g.*, Bluetooth, and WiFi). The vital signs, collected by these sensors, are either analyzed at the smartphone end or transmitted to a remote server for further data analysis.

We will discuss a series of work exploring non-motor symptoms monitoring. Even though they are not proposed for PD detection, they still provide thoughts towards PD detection in daily life.

Sleep Disorder: Due to the growing problem of insomnia, sleep conditions monitoring attract the attention recently. In the past several years, researchers showed that built-in sensors of a smartphone, such as a gyroscope, magnetometer, and accelerometer, can help achieve sleeping conditions monitoring [49]–[51]. The gyroscope and accelerometer help detect the movement and gestures during sleeping. The magnetometer achieves sleep orientation detection. The microphone can record different voice activities in the sleep, which can reflect different sleeping stages. Some researchers also propose to utilize wireless signal into the detection of different sleeping stages, which works by monitoring the changed waveform caused by the altered breathing and altered sleeping posture [52].

Mood Disorder: Mood detection through model devices attracts much attention for its enormous potential in the psychology domain. The existing approaches can conclude into three folds. First, the built-in accelerometer of a smartphone can detect happiness or sadness by detecting the movement variation of a person [53]. Second, a built-in microphone can help detect the emotion by measuring the audio features [54]. The features will include but not limit to loudness, timbre, pitch, and tone. They can well reflect the users' emotions and possibly reveal the symptoms of depression or anxiety. Facial expression recognition is another common way to detect mood [55]. When people look at videos, the built-in camera can record their facial activity. Then, state-of-the-art CV technology can analyze the facial expression and gaze direction to understand their mood level.

C. Summary

We highlight some significant work about vocal impairment detection in Table II. At the very beginning, vocal impairment detection was achieved in an experimental environment where the noise level was strictly controlled. Along with the increase of knowledge about the voice, researchers proposed to use mHealth systems to facilitate daily-life PD detection. Meanwhile, advanced technologies, such as deep learning, were proposed to achieve high accuracy of PD detection.

Compared with vocal impairment, other non-symptoms (*e.g.,* pain, sleep disorder, and depression) did not receive enough attention yet. This is mainly due to the restriction of existing mobile devices to access those types of data. We highlight some preliminary work, including sleep stages tracking and mood disorder detection, and we hope that they can stimulate the research of early detection of PD in the future.

VI. Multidomain Detection

Because parkinsonism is a clinical syndrome characterized by multiple symptoms, focusing on multiple symptoms than using a single sensing modality is considered to achieve higher accuracy of PD detection.

Sharma *et al.* [56] and Arora *et al.* [57] achieved multiple symptoms monitoring using a smartphone. They used the built-in microphone to record voice for vocal impairment detection and used the built-in accelerometer and gyroscope to collect the gait information for movement impairment detection.

Specifically, Sharma *et al.* designed a protocol named SPARK, which takes advantage of a synergistic combination of a smartphone and a smartwatch to monitor dysfunctional speech, gait abnormalities, limb dyskinesia, and voice disorder. Besides PD detection, SPARK also supports Telemanagement for patients with PD. Through the information provided by the smartphone, physicians can adjust their therapeutic schedule. However, one limitation reported by the authors is compatibility. Since all the participants are elders, they felt strange about emerging mobile devices such as smartwatches and smartphones. In their experiment, the misplacement of sensors, data log errors, and device malfunction happened during the experiments.

Arora and his group presented a pilot study of detecting and monitoring multiple symptoms of PD using a smartphone application (APP). To comprehensively understand the conditions of a subject with PD, the authors monitored multiple symptoms,

TABLE II
OVERVIEW OF THE SELECTED PUBLICATIONS STUDYING VOCAL IMPAIRMENT. THE CLASSIFICATION PROBLEM IS PD/HEALTHY CLASSIFICATION

Authors	#Sub.	#Sam.	Voice Genre	Feature	Classifier	Best Acc.
Little *et al.* [38]	31	195	Sustained Vowels	Global Features	SVM	91.4%
Sakar *et al.* [39]	40	-	Words and Sentence	Global Features	SVM	77.5%
Jeancolas *et al.* [40]	74	1110	Vowels and Reading	MFCCs	SVM	91.4%
Zhang *et al.* [41]	20	1000	Sustained Vowels	Spectrogram	CNN	90.5%

TABLE III
OVERVIEW OF THE PD DETECTION APPLYING MULTIDOMAIN SYMPTOMS

Authors	# of Subjects	# of Samples	classification Problem	Device
Sharma *et al.* [56]	-	-	PD/Health Detection	Smartphone & Smartwatch
Arora *et al.* [57]	20	1772	PD/Health Detection	Smartphone
Zhan *et al.* [58]	226	8000	PD Medicine Response Detection	Smartphone
Zhan *et al.* [59]	129	6148	PD Severity Estimation	Smartphone

TABLE IV
A COMPARISON OF DIFFERENT APPROACHES FOR PD DETECTION/MONITORING

Methods	Sensors/Sensing Modality	Problem Description	Is Privacy Preserving	User Adherence
Gait Analysis	Smartphone	PD Monitoring	○	○
	Inertia Sensor	PD Monitoring	○	●
	Webcam	PD Monitoring	●	●
Tremor Analysis	Smartphone/Smart-pen	PD Detection/Monitoring	○	●
Voice Analysis	Free Speech	PD Detection/Monitoring	●	○
	Sustain Vowels	PD Detection/Monitoring	○	○
	Reading	PD Detection/Monitoring	○	●

○ = Yes/High ● = No/Low

such as voice disorder, posture unbalance, gait, tremor, and cognitive performance, by implementing five separate tasks in their smartphone APP. Considering the low user adherence reported by previous work, all the tests in their APP are short and cost less than 5 minutes in total. In order to evaluate their method, they enrolled 20 participants (10 PD and 10 controls) in total and collected 1772 samples. Their Random Forest model achieved an average sensitivity of 96.2±2% and an average specificity of 96.9±1.9%.

Zhan *et al.* [58] published an extended work to understand whether the smartphone-based measurement can be a solution to the remote monitoring of medication response. Instead of collecting data by enrolling people locally, they used an entirely remote method to recruit 226 individuals (121 PD and 105 controls) online and collected 8000 samples in total. They also proposed a method for passive monitoring by continuously collecting data from the accelerometer, gyroscope, GPS location, and phone usage to measure the PD severity. The authors published an extension [59] in 2018, where they proposed an objective measurement of PD severity and tested construct validity. Typically, they evaluated the ability to capture intraday symptom fluctuations, correlating with current standard PD outcome measures, and responding to dopaminergic therapy.

So far, we comprehensively review the mHealth technologies used towards PD detection. Table IV summarizes the mHealth technologies in terms of sensors/sensing modality, user adherence, detection/monitoring classification, and privacy concerns. In the following sections, we will identify the research challenges and potential opportunities.

VII. RESEARCH ISSUES AND CHALLENGES

In this section, we summarize the common issues and challenges in existing researches.

A. Users Adherence

Continuous user monitoring is essential to identify the minor variance caused by PD in the early stages. Although existing work can achieve such a kind of longitude and continuous monitoring in a nonclinical environment, many studies report that users show low engagement in their experiments. For example, Lima [60] presented a detailed study of the user's compliance. The authors performed a 13-week-long experiment in both the Netherlands and North America. They adopted smartphones and smartwatches to collect tremors and activity at night. Their results show that the median compliance rate in the Netherlands is 68%, and this number is 62% in North America. The rate of accelerometer data declined 23% after 13 weeks, and this number became 27% after a six-week experiment in North America. 38% of the testers reported their reasons for low compliance is "Personal Circumstances," and 34% reported that "System is too complex to use." The mPower study [61] performed a

6-month-long experiment in the United States. They adopted smartphones to collect FOUR activities (i.e., voice, gait, finger tapping, memory). Their study reveals that more than 50% of people give up data collection thoroughly after five days.

B. Active and Passive Sensing

Most existing works, as we mentioned, adopt an active sensing-based solution, and user adherence is not high. Passive sensing becomes a possible solution to achieve high user adherence. However, the gap in performance between passive and active sensing is still not clear yet. Although a few authors [19], [20], [23] explored the passive sensing protocols for PD detection. Few experiments showed if performance in the passive sensing-based methods can reach the same level as those in active sensing.

C. Non-Motor Symptoms Detection

The development of mHealth systems provides opportunities for more and more researchers to examine the impact of PD on motor symptoms (*e.g.*, tremor, postural instability, rigidity, bradykinesia). Although the performance (*e.g.*, accuracy, sensitivity, and specificity) of PD detection is improved progressively, they provide little help in the early detection of PD. Because motor symptoms usually appear in the mid-stage of PD when 70% neurons are permanently dead. On the contrary, few types of research focus on the studies of non-motor symptoms (*e.g.*, depression, anxiety, sleep disorder, apathy, stomachic dysfunction, and hyposmia), which are considered to emerge in early stages. The reason is that those non-motor symptoms are usually hard to be directly measured by wearable sensors. For example, exploring the stomachic dysfunction usually requires laboratory-based instruments, and there exist no available solutions for a smartphone to achieve this task nowadays. Accordingly, there exists an urgent need to design an accessible solution, including new sensors and methodology, for daily-life non-motor symptoms detection.

D. Collect More Data

The unbalanced dataset is another big issue. We observe that the same classification model can present an entirely different performance on two different datasets. Considering the example of vocal impairment, Little *et al.* [38] and Sakar *et al.* [39] claimed that sustained vowel achieves a better performance than any other types of voice. However, Jeancolas *et al.* [40] received a different result, where the reading task achieves the best performance. The reason comes from the biased dataset in two experiments. A possible solution is to collect as much data as possible, but the large-scale data collection is still an unsolved problem.

E. Generalized Classifier

The performance of the classification model is also biased nowadays. Although Tsanas *et al.* [62] and Jafari *et al.* [63] claimed that they achieved an accuracy of 99% and 97.5% separately when employing sustained vowel into PD detection, Jeancolas *et al.* [40] pointed out that the proposed validation approach is speaker-dependent. Although the samples in training and testing set a contrast with each other, they can correspond to the same person. This validation method can lead to an over-optimistic result. In the experiments of Jeancolas, the authors claimed this accuracy can even decrease to 60% if the validation process is speaker-independent.

F. Privacy-Preserving Protocol

Last but not least, privacy-preserving is a big concern when we discuss daily-life PD detection. To achieve high user adherence, one efficient way, as we mentioned, is to collect some PD-related data from users passively. For example, we can wake up the GPS and accelerometer all the while to monitor the movement disorder, and we can continuously turn on the built-in microphone monitor the voice. However, there is much more than that. On the one hand, these methods massively intervene in the lives of people due to privacy disclosure. On the other hand, it is hard to extract data which is privacy-irrelevant but still reveals the PD symptoms. In the paper [58] we mentioned above, the authors passively collected 46,000 hours of data from 226 individuals, however, how to make use of these data is still not clear.

VIII. Opportunities

In this section, we discuss the opportunities for early PD detection in daily life. We first discuss the possible privacy-preserving protocol for passive sensing. Then, we discuss the solutions for non-motor symptoms detection.

A. Passive Sensing Protocol

Although passive sensing can increase user adherence, it brings a serious privacy-related problem. In an end-to-end system, we propose two protocols to address this problem.

Privacy-isolation Zone: In an end-to-end system, sensors such as GPS, accelerometer, and microphone can not only acquire data that reveal the symptoms of PD but leak the privacy simultaneously. One solution is to isolate the privacy content in the user end. For example, since speech is considered as an early indicator of PD, it is possible to isolate the privacy-sensitive content in the user end [64]. Techniques, such as encryption, content filter, and compressed sensing, can well isolate the privacy-sensitive content meanwhile reserving the content which reveals the PD risk.

Embedded AI: Embedded AI can be another solution. In order to achieve a better performance in PD detection, deep learning is considered as a better tool. However, due to the limitation of the computation ability and battery, the model for PD detection is usually implemented in the server end, while the mobile end is only responsible for collecting data. In this case, privacy-sensitive data can leak, and users' privacy cannot be protected. Fortunately, the development of AI techniques, such as MobileNets [65], make PD detection in the user end possible. Without transmitting data to a cloud server, the mobile end can be responsible for both data collection and PD detection in the future.

B. Innovate Sensing Modalities for Non-Motor Symptoms Detection

Detection of Sleep Disorders: Monitoring the sleep disorder with mHealth technologies becomes an available solution to achieve early detection of PD. Hao *et al.* [66] proposed an unobtrusive approach by adopting the built-in microphone to monitor the sleeping condition, and they claim to achieve an accuracy of 90% to track various events during a night. Zhao *et al.* [52] proposed a new approach utilizing wireless signal instead of an acoustic signal to monitor the sleep stages, and they achieve the best accuracy of 79.8% to classify different sleep stages.

Detection of Mood Disorders: Anxiety and depression are considered as one of the earliest symptoms of PD. Although directly measuring these symptoms is hard, it is possible to infer the conditions of mental health by monitoring smartphone usage. Given an example, we can monitor the time of smartphone usage during a day to predict the risk of depression and monitor the movement of a user during and before the calling to predict the risk of anxiety [67].

IX. Conclusion

This review carries the current state-of-the-art work utilizing mHealth technologies into PD detection. In this paper, a range of approaches for detecting motor and non-motor symptoms are described. Further, the present challenges and opportunities have been discussed, providing insights for further research.

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