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The Emerging Wearable Solutions in mHealth

Fang Zhao, Meng Li and Joe Z. Tsien

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Abstract

The marriage of wearable sensors and smartphones have fashioned a foundation for mobile health technologies that enable healthcare to be unimpeded by geographical boundaries. Sweeping efforts are under way to develop a wide variety of smartphone-linked wearable biometric sensors and systems. This chapter reviews recent progress in the field of wearable technologies with a focus on key solutions for fall detection and prevention, Parkinson's disease assessment and cardiac disease, blood pressure and blood glucose management. In particular, the smartphone-based systems, without any external wearables, are summarized and discussed.

Keywords: wearable inertial sensors, accelerometer, gyroscope, ECG patch, classification algorithm, smartphone, fall detection and prevention, Parkinson's disease, cardiac rhythm, blood glucose, blood pressure

1. Introduction

Nowadays, dramatic advances in microelectromechanical systems (MEMS) technology have paved the way for wearable sensors to make inroads into mHealth, providing the potential for medical care and research to take place outside the standard doctor's office or hospital. A wide variety of wearable biometric sensors, such as bracelets, watches, skin patches, headbands, earphones, and clothing [1, 2], have been designed and developed. Regardless of the various forms and functions of these sensors, their unifying design focus is to allow for unobtrusive, passive, and continuous monitoring. Beyond sensing capability, another key characteristic is their ability to seamlessly connect with a mobile device to transfer all biometric data into a software application (APP) that can be shared with healthcare providers, researchers or family members. Inertial sensors, the most ubiquitous wearables, combined with dedicated algorithms are able to "count" steps (i.e., pedometers), gauge physical activity levels, indirectly

estimate energy expenditure [3], and implement activity recognition [4]. Today, the Holter monitor, the most commonly used ambulatory electrocardiography device for assessing cardiac abnormalities, is one of the technologies that may soon become obsolete, since prolonged continuous rhythm monitoring is available by wearing an electrocardiogram (ECG) patch on the chest [5]. Other notable examples of sensor technologies under development which allow for a more personalized understanding of our health include cuffless blood pressure monitoring and noninvasive blood glucose tracking. Through progressively miniaturized, smartphones are equipped with comparatively advanced sensing capabilities (i.e., accelerometer, gyroscope, magnetometer, camera, and many more) and powerful computing capabilities, making it the ideal platform for remote health monitoring without the extra expense of purchasing and inconvenience of using dedicated wearables. As a result, smartphone-based solutions have emerged most recently for fall detection and prevention [6], activity recognition [7], Parkinson's disease (PD) assessment [8], and cardiac rhythm measurement in mHealth.

This chapter provides a review of recent progress in the field of wearable systems and solutions that have already entered into or have the potential to apply in mHealth. Aging of the population is a global issue, and it presents tremendous challenges to society and healthcare systems all over the world. The most common healthcare issues of the aging population include the following: (i) falls that are considered as one of the major hazards for the elderly, especially for those living alone [9]; (ii) neurological disorders that are categorized as major chronic diseases inducing motor impairments, with PD as one of the most frequently occurring conditions [10]; and (iii) cardiac disease, hypertension and diabetes are the most common chronic diseases affecting the elderly [11]. Therefore, a critical analysis of the state-of-the-art wearable solutions for these age-related care issues and chronic diseases are presented.

The remainder of this chapter can be separated into five sections. The wearable solutions for motion monitoring are discussed in Section 2. Firstly, the basic architecture of the wearable motion monitoring systems is described, followed by a summary of the state-of-the-art smartphone-based fall detection and prevention systems, with a focus on the sensor used, extracted features, the classification algorithm, and the outcomes in each system. The wearable solutions for PD are then discussed. A selection of external wearable solutions and smartphone-based systems that used pattern recognition algorithms to classify motor signs of functional activities impairment in PD are presented and compared. Section 3 illustrates the wearable solutions for cardiac activity monitoring. Several commercially available portable devices are presented. Section 4 describes the approaches for cuffless blood pressure monitoring and noninvasive blood glucose monitoring. Unfortunately, these approaches are not satisfactory to date. Finally, conclusion offered in Section 5 points out important observations and areas that need further research.

2. Wearable solutions for motion monitoring

Mirroring the increasingly widespread adoption of wearable inertial sensors in personalized healthcare is an equally remarkable development in algorithms to classify human activity [7].

As a result, inertial sensor technologies can go well beyond step counts to a wealth of person-alized activity information to help guide health and wellness. Earlier work by Bouten *et al*. [12] established a significant relationship (*r*=0.89) between accelerometer output and energy expenditure due to physical activity, impelling wearable sensor to become capable of estimat-ing energy expenditure in diabetes or obesity management. Subsequent work by Najafi *et al*. [13] founded a significant correlation between postural transition (PT) and falling risk using a gyroscope, which led to a variety of other works to exemplify the prominence of wearable inertial sensors in fall detection and prevention in elderly care. The activity recognition by wearable inertial sensors has also been used in the assessment and rehabilitation of many neurological diseases [14], such as Parkinson's disease (PD), stroke, cerebral palsy (CP), multiple sclerosis (MS), and Huntington's disease (HD), which can induce motor impairment. Transformations are under way in movement monitoring to provide care in the daily lives of those afflicted with these diseases as a result of all these breakthroughs.

2.1. Architecture

The basic architecture of motion monitoring systems for mHealth consists of three common phases namely, sensing, processing and communication (**Figure 1**). Feature extraction and motion classification algorithm used in the processing phase may differ greatly from system to system.
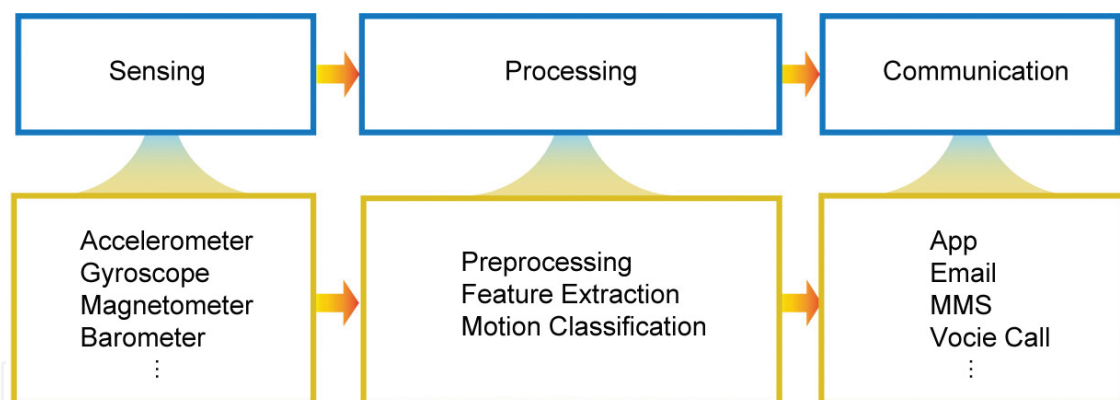
Figure 1. Basic architecture of activity tracking systems for mHealth.

2.1.1. Sensing

Multimodal MEMS sensors can be utilized to identify physical activities, including acceler-ometer, gyroscope, magnetometer, barometer, etc. The terms accelerometer, gyroscope, and magnetometer will refer to triaxial accelerometers, triaxial gyroscopes and triaxial magneto-meters, respectively, unless otherwise stated. Each type of sensor is sensitive to a kinematic quantity: accelerometer for sensing acceleration along three orthogonal directions; gyroscope for detecting angular momentum; magnetometer for gauging changes in orientation by measuring the strength of the local magnetic field along three orthogonal axes; and barometer for determining rapid changes in altitude (e.g., walking up/down stairs) by measuring absolute

atmospheric pressure to infer altitude above sea level. Their combination can even estimate three-dimensional (3D) orientation and displacement.

2.1.2. Processing

The processing phase encompasses preprocessing, feature extraction and physical motion classification steps. Preprocessing needs to be first applied to the raw data collected from MEMS sensors to improve the signal-to-noise ratio. The signals are often smoothed by median filters of a short sliding window to remove spurious noise [15]. Accelerometer data are often high-pass filtered to separate acceleration caused by gravity from acceleration due to body movement [16].

After preprocessing of MEMS data, features are generally extracted from sequential epochs of time using window techniques. The most commonly used approach is the sliding window often with 50% overlap between consecutive windows [17], which is the most suitable for real-time or online applications. Statistical measures of the time domain and frequency domain features are widely used to reduce the MEMS data of each window epoch to a finite number of derived parameters from which a physical movement can be inferred.

Prior to classification, feature selection techniques [18] may be applied to find the optimal feature subset, which can best distinguish between movements, from all of the features generated. Feature selection is of particular importance as inappropriate or redundant features may deteriorate the overall classification performance. The selected features from the MEMS sensor data are exploited by the classification algorithms in the development of a model that can identify specific physical movements. Classification methods used in activity recognition include (but are not limited to) hidden Markov models (HMM), K nearest neighbors (KNN), support vector machines (SVM), discrete wavelet transform (DWT), decision tree classifiers (DTC), random forests (RFs), linear discriminant analysis (LDA) or feed-forward neural network (Bpxnc).

2.1.3. Communication

After processing, the classified motion data can then be sent to medical staff (e.g., a caregiver or a physician) for remote monitoring or back to the user or patient for self-monitoring. Once an abnormal movement (i.e., fall event) is detected, the wearable mHealth systems sent out a signal to seek help from the monitoring center or a caregiver via smartphones.

2.2. Fall detection and prevention

Falls are one of the major causes of injuries and hospital admissions of elderly people. Those who suffer from neurological diseases (e.g., stroke, PD) also give rise to increased fall risks. Falls can potentially cause severe physical injuries, such as bleeding, fracture and central nervous system (CNS) damage, and long lie times (remaining involuntarily on the ground for a prolonged period) after the fall can lead to disability, paralysis, even death. Therefore, the first line of defence against fall hazards is to prevent them and the second line of defence is to provide emergency treatment in time.

2.2.1. Smartphone-based systems

Initially, dedicated wearable kinematic sensors have been developed with the ability to assist in identifying falls [19, 20] and estimating the likelihood of future falls by monitoring activity levels or analyzing the individual's gait [21, 22]. However, their widespread adoption has been limited by the cost associated with purchasing the device and the low utilization coefficient by the user (who may often forget or refuse to wear the specially designed wearables). There has been a shift toward smartphones in recent years, as the smartphone with multimodal built-in MEMS sensors, coupled with its ubiquitous nature and increased computational power, make it the ideal platform for fall monitoring in mHealth. The first smartphone-based fall detection app iFall [23] utilized an integrated accelerometer to recognize the difference in position before and after the fall. Later in 2010, the PreFallD [24] was developed considering both the wearer's acceleration and orientation during the fall event. **Table 1** summarizes and compares the features of the existing smartphone-based fall detection and prevention systems or applications. The literatures that presented very preliminary investigations and did not declare the performance of their proposed solutions are not included here.

Article	Application	Sensors (Placement)	Algorithm	Performance	Notification (Information)
[23]	Detection	Accelerometer (Any)	Threshold	Demonstrated fall can be detected by smartphone.	SMS (time, GPS coordinates), audible notification.
[24]	Detection	Accelerometer & gyroscope & magnetometer (chest, waist, thigh)	Threshold	2.67% (Average FN), 8.7% (Average FP)	Audio alarm, voice call.
[25]	Detection	Accelerometer (trouser pocket)	DWT	85% (RC), 95% (PR)	SMS (GPS coordinates), email (Google map), twitter.
[30]	Detection	Accelerometer (chest, waist, thigh)	Threshold	97% (PR), 2.67% (average FN), 8.7% (Average FP)	Audio alarm, voice call
[26]	Detection	Accelerometer (Waist)	C4.5 DT, NB, SVM	98.85% (AC for DT); 86.47% (AC for SVM); 87.78% (AC for NB)	SMS
[97]	Detection	Accelerometer (waist)	Threshold	Detected 54 out of 67 simulated falls.	Email, SMS.
[31]	Detection	Accelerometer (waist)	Threshold	0.81 (SP), 0.77(SE)	SMS (time, location)

Arti cle	Appli cation	Sensors (Placement)	Algorithm	Performance	Notification (Information)
[39]	Detection	Accelerometer & gyroscope (hand, shirt, or trouser pocket)	Threshold, One-class SVM	75% (AC for hand); 77.9412% (AC for shirt pocket); 84.2857% (AC for trouser pocket)	Undisclosed
[98]	Detection	Accelerometer (waist)	Threshold	Capability of differentiate between running and falling	SMS (time, GPS coordinates)
[44]	Detection	Accelerometer (waist)	Threshold, ANN	100% success rate for a total of 500 epochs.	Message (GPS coordinates)
[6]	Detection, prevention	Accelerometer & gyroscope (waist)	Threshold	The uFall and uTUG can ran on a smartphone to realize long-term and real-time monitoring.	Audio alarm, email, SMS.
[99]	Detection	Accelerometer (shirt, or trouser pocket)	Threshold	97% (average SE), 100% (average SP)	Undisclosed
[32]	Detection	Accelerometer (Shirt pocket)	threshold	92.75% (SE), 86.75% (SP)	Text message
[40]	Detection	Accelerometer (trouser pocket)	SVM	95.7% (PR), 90% (average RC)	vibration, audio alarm, SMS (time, location)
[27]	Detection	Accelerometer & gyroscope (hand, pocket, waist)	Semisupervised learning	85.3% (SE), 90.5% (SP)	Undisclosed
[33]	Detection	Accelerometer (chest, waist, thigh)	Threshold	72.22% (SE), 73.78 (SP)	SMS
[34]	Detection	Accelerometer & gyroscope (hand, pocket)	Threshold	80% (SE), 96.25% (SP), 85% (AC)	Undisclosed
[41]	Detection	Accelerometer & Wi-Fi module (waist)	DT, SVM, NB, RSSI	100% & 75.8% (PR & RC for DT); 99.81% & 75.43% (PR & RC for SVM); 98.67% & 73.20%	SMS (name, time, location)

Arti cle	Appli cation	Sensors (Placement)	Algorithm	Performance	Notification (Information)
				(*PR* & *RC* for NB).	
[28]	Detection	Accelerometer & gyroscope & magnetometer (chest)	Fisher's discriminant ration and *J*3 criterion, hierarchical classifiers	97.63% (*AC*) for fall; 95.03% (*AC*) for total	MMS (time, GPS coordinate, map)
[35]	Detection	Accelerometer (waist)	Threshold	83.33% (*SE*), 100% (*SP*)	SMS, voice call, twitter, email, Facebook
[100]	Detection	Accelerometer (waist)	Threshold	Detected 47 out of 50 samples.	SMS (time, GPS data)
[29]	Prevention	Accelerometer & gyroscope (trouser pocket)	C4.5 DT, Hjorth mobility and complexity	99.8% (*AC*)	Message, vibration
[42]	Detection	Accelerometer (trouser pocket)	OneR, ReliefF, SCMA, K*, C4.5, NB	90% success ratio, 83.8% & 82.0% (*PR* & *RC* for NB); 83.8% & 82.0% (*PR* & *RC* for J48 DT); 88.9% & 88.6% (*PR* & *RC* for K*).	SMS (GPS coordinate)
[36]	Detection	Accelerometer (waist)	Threshold	90% (*SP*), 100% (*SE*), 94% (*AC*)	SMS
[37]	Detection	Accelerometer & encompass (pocket)	Cascaded classification	92% (*SE*), 99.75% (*SP*)	Message (GPS coordinate)
[38]	Detection	Accelerometer (side, or back pocket, arm, neck)	Threshold & orientation	95% (*PR*), 90 (*AC*), 100% (*RC*)	Undisclosed
[43]	Detection	Accelerometer (Pocket)	PNN[1], PSVM[2]	PNN: 0.9861 (mean AUC); PSVM: 0.9914 (mean AUC)	Undisclosed

[1]PNN-Personalized Nearest;
[2]PSVM-Personalized SVM.

Table 1. Smartphone-based fall detection and prevention systems.

The most common sensor used in fall detection and prevention was the accelerometer, followed by the gyroscope (**Table 1**). In most of the studies, threshold-based algorithm was adopted for fall detection due to its low complexity. The most commonly used feature for threshold-based algorithm is the magnitude vector of acceleration signal:

$$| A_T | = \sqrt{| A_x |^2 + | A_y |^2 + | A_z |^2} \tag{1}$$

where A_x, A_y, and A_z represent accelerometer signals of the x-, y-, and z-axis, respectively. The threshold value could be predefined (fixed) or adaptive (changed with user-provided physiological data, such as height, weight).

The surge in computing power has fashioned a foundation for complex machine-learning classification algorithms for fall detection and prevention to be implemented in smartphones. The classification algorithms used in the processing phase vary considerably across systems. Yavuz et al. [25] utilized DWT and achieved a better true-positive (TP) performance while decreasing the false positives (FP) when compared to threshold-based algorithm. Zhao et al. [26] implemented three machine-learning algorithms—namely C4.5 DTC, NB, and SVM and compared their performances based on recognition accuracy. Fahmi et al. [27] designed a semisupervised algorithm to detect a genuine fall event with smartphone. He and Li [28] employed a combined algorithm of Fisher's discriminant ratio (FDR) criterion and J3 criterion for feature selection and hierarchical classifiers to recognize 15 activities including fall events. Majumder et al. [29] applied Hjorth mobility and complexity to identify high-risk gait patterns, hence developed a fall prevention system called iPrevention.

Once a fall event is detected, the systems send out notifications including audible alarms, vibrations, automatic voice calls, short message service (SMS), multimedia messaging service (MMS), E-mails, Twitter messaging, etc., (**Table 1**). Notification messages may contain information regarding time and location (GPS coordinates or Google Map).

2.2.2. Performance evaluations

There is no uniform standard for outcome evaluations of fall detection or prevention systems now. The outcomes are often represented by four possible situations [24, 30]: *TP*, a fall occurred and was correctly detected; *FP*, the system declared a fall that did not occur; true negative (TN), a fall-like event was not misclassified as a fall event; false negative (FN), a fall occurred, but the system missed it. The reliability of systems is usually evaluated based on the following parameters: sensitivity (*SE*) = *TP*/(*TP*+*FN*), which is the ratio of fallers correctly classified as fall event [27, 31–34]; specificity (*SP*) = *TN*/(*TP*+*FN*), which is the ratio of fall-like events correctly classified as nonfallers [35–38]; accuracy = (*TP*+*TN*)/(*TP*+*FP*+*FN*+*TN*), which is the ratio of true results in the whole data set [26, 28, 29, 39]. Some works measured the performance in a different way; they utilized *precision* = (∩)/and recall—namely, the number of correct results divided by the total outputs—as the performance indexes [40–42]. Some other works evaluated the proposed system by measuring the area under the receiver operating characteristic curve (AUC), where the curve represented *SE* versus *FN* [43].

2.2.3. Limitations and challenges

Despite the expanding body of evidence to support the use of smartphones for fall detection and prevention, it is important to recognize the limitations in this area of science. The prominent weakness is problems induced by the limited battery life of the smartphone. The rate at which the smartphone's battery is consumed is dependent on both internal and external factors. Internal factors are built-in sensor dependent, including the sampling rate and resolution mode. High-resolution mode can dramatically increase the rate of power consumption. External factors are related to the number of sensors used, data recording time, and complexity of the algorithms. Mellone *et al.* [6] showed that a battery could power a smartphone (Samsung Galaxy S II) for 30 h with only one sensor used and 16 h with three sensors activated. Majumder *et al.* [29] reported that a fully charged battery can only power an iPhone for 3 h at the most, when running a machine learning algorithm. Energy efficiency will continue to be an important criterion when choosing the algorithm, unless advancements in battery technology could lead to higher density energy storage.

Model	Sensors	Dynamic ranges	Resolution
Samsung S4	Accelerometer	±2 g	±0.001 ms^{-2}
	Gyroscope	±500°/s	±0.057°/s
	Magnetometer	±1200 μT	±0.15 μT (x/y axis) ±0.25 μT (z axis)
	Barometer	300–1100 hPa	±1 hPa
Samsung S3	Accelerometer	±2 g	±0.01 ms^{-2}
	Gyroscope	±500°/s	±0.015°/s
	Magnetometer	±1200 μT	±0.30 μT
	Barometer	260–1260 hPa	±0.24 hPa
Galaxy Nexus	Accelerometer	±2 g	±0.61 m·s^{-2}
	Gyroscope	±2000°/s	±0.06°/s
	Magnetometer	±800 μT	±0.15 μT (*x/y* axis) ±0.30 μT (*z* axis)
	Barometer	300–1100 hPa	±1 hPa
HTC One	Accelerometer	±4 g	±0.039 m·s^{-2}
	Gyroscope	±2000°/s	±0.06°/s
	Magnetometer	±4900 μT	±0.15 μT
LG Nexus 4	Accelerometer	±4 g	±0.001 m·s^{-2}
	Gyroscope	±500°/s	±0.015°/s
	Magnetometer	±4912 μT	±0.15 μT
	Barometer	0–1100 hPa	±1 hPa
iPhone 5/5s	Accelerometer	±8 g	±0.002 m·s^{-2}
	Gyroscope	±2000°/s	±0.06°/s
	Magnetometer	±1200 μT	±0.30 μT
iPhone 6/6plus	Accelerometer	±8 g	±0.002 m·s^{-2}
	Gyroscope	±2000°/s	±0.06°/s
	Magnetometer	±4900 μT	±0.15 μT
	Barometer	300–1100 hPa	±0.16 hPa

Table 2. Specifications of the built-in sensors in some currently available smartphones.

The resolution and dynamic range of the built-in inertial sensors vary considerably across smartphones (**Table 2**). Acceptable dynamic ranges for accelerometers from ±4 g to ± 16 g (g = 9.81 ms^{-2}) have been reported for fall detection applications [35, 44], which is beyond the typical dynamic ranges of most currently available smartphone accelerometers (± 2 g). The newest high-end commercially available smartphones (i.e., iPhone 6/6plus) have accelerometers with higher dynamic ranges (± 8 g), making these devices more suitable for detecting falls.

In addition, a major limitation of using smartphones to detect fall is that it requires the smartphone to be consistently located and/or oriented in the same position. It may be difficult to do so due to the multifunctional nature of smartphones. Habib *et al*. [45] showed that individuals may not place their smartphone on their body whilst at home so, that being said, it may limit the ability of the smartphone to detect fall in the home. At present, smartphone placement and usability issues should be handled carefully.

2.3. Functional activities assessment for Parkinson' s disease

For a population that is shifting toward an older age range, PD is categorized in the most common chronic neurological disorders. PD is characterized as an age-related neurodegenerative disorder due to the loss of dopamine-producing brain neurons, an important neurotransmitter involved in the regulation of movement. Progressive tremor, bradykinesia, hypokinesia, rigidity, and impaired postural control are common and disabling features of most patients with PD. The motor disorder analysis is generally performed in a clinical setting to provide subjective assessments. However, the motor fluctuation measurements in the clinical setting might not precisely reveal the real functional disability experienced by patients in natural environment. With the existing and on-going advance developments in MEMS technologies, continuous, unsupervised, objective and reliable monitoring of mobility and functional activities in natural environments is now possible, allowing for long-term, home-based intensive care and improvement of the individual healthcare and well being.

2.3.1. Wearable inertial sensor-based methods

A growing body of literature studied the use of wearable inertial sensors to detect and quantify tremor, bradykinesia and levodopa-induced dyskinesia (LID) in PD populations. Most studies were focused on finding the features derived from sensor signals that are effective for detecting differences between people with PD and healthy controls [46–49]. Results from these studies presented a range of outcomes which included the root mean square (RMS) of accelerations, the deviation of acceleration, step or stride variability, gait regularity or symmetry, FFT features, entropy and many more. Only a few works established and validated motion analysis methods or systems that used pattern recognition algorithms to classify motor signs of functional activities impairment in PD. **Table 3** provides a detailed comparison of these different methodological approaches. Leave-one-subject-out method and cross-validation method were used for validating the approaches.

Arti cle	Sensors (Placement)	Algorithm	Features	Performance	Validity
57	Accelerometer & gyroscopes (shanks, trunk)	Logistic regression model with Mamdani fuzzy rule-based classifier	Duration of transition, amplitude, range, minimum value, maximum value, relative time.	Differentiate between sit-to-stand and stand-to-sit transitions with 83.8% SE.	Cross-validation
52	Accelerometer (limbs, trunk, belt)	KNN, Parzen, Parzen density, binary decision tree, Bpxnc, SVM.	RMS, range.	Detect the severity of bradykinesia with an AC range of 70–86% depending on the algorithm.	Cross validation
55	Accelerometer & gyroscopes (wrist, thigh, foot, sternum)	DT	IAA[1] and change in thing inclination per second (thigh); differentiate an upright position from a horizontal one (trunk, thigh); AAM[2] (wrist); peak detection (foot).	98.9% (overall AC); Detect significant changes in rest and kinetic tremor with an AC range from 78.8–94.1% depending on the activity performed.	Leave-one-subject-out method
53	Accelerometer & gyroscopes (shoes)	Boosting with decision stump, LDA and SVM with linear and RBF kernel.	Step duration, entropy, variance, energy ratio, 0.5–3 Hz energy band.	Classify patients with PD and healthy controls using LDA with 88% SE and 86% SP; Distinguish mild from severe gait impairments with 100% SE and SP.	Leave-one-subject-out method
54	Accelerometer & gyroscopes (shoes)	LDA, AdaBoost, SVM with linear and RBF kernel.	Single steps, complete gait sequence, FFT of gait sequences.	Distinguish patients with PD from controls with an overall AC of 81%; Differentiate between Hoehn and Yahr III patients to controls with 91% AC.	Cross validation
51	Accelerometer	Supervised machine-learning models	FFT features: P_{total} between 0.5–8 Hz, $P_{locomotion}$	94.94% (AC), 94% (SP)	Undisclosed

Arti cle	Sensors (Placement)	Algorithm	Features	Performance	Validity
			on 0.5–3 Hz, P_{freeze} on 3–8 Hz, freeze index.		
56	Four accelerometers (extremity) and one accelerometers & gyroscopes (waist)	HMM (for tremor)	Time, frequency and spatial features.	87% (*AC*), 0.008 (*MBE*)	Leave-one-subject-out method
		DT (for LID)	Mean value, standard deviation, entropy, energy in specific frequency subbands, entropy.	85.4% (*AC*), 0.31 (*MBE*)	
		SVM (for Bradykinesia)	Approximate entropy, sample entropy, RMS, cross correlation, range.	74.5% (*AC*), 0.25 (*MBE*)	
		RF (for FOG)	Entropy	79% (*AC*), 0.79 (*MBE*)	

[1]IAA-Integrals of the absolute value of the accelerometer output;
[2]AAM-active arm movement.

Table 3. Wearable inertial sensor-based methods for Parkinson's disease.

These methods were founded on various machine-learning classifiers. Salarian *et al*. [50] applied a fuzzy classifier combined with a logistic regression model to categorize sit-to-stand (STS) transitions. Three inertial sensors were used to detect the kinematic features of the trunk movements during the transitions. Compared to video recordings reference system, it demonstrated the ability to differentiate sit-to-stand from stand-to-sit with a sensitivity of 83.3% in PD and 94.4% in controls. Another study by Mazilu *et al*. [51] presented the GaitAssist system to detect FoG with two ankle-mounted IMUs, streaming data via Bluetooth to an Android phone. Supervised machine-learning models, trained offline using several FFT features, were utilized with an overall FoG hit rate of 94.94% and a specificity of 94%.

Some studies, on the other hand, evaluated various classifiers to identify ambulatory activities. Cancela *et al*. [52] implemented six activity recognition algorithms, —namely KNN, Parzen, Parzen density, DTC, Bpxnc, and SVM, to detect the severity of bradykinesia and found out that the SVM revealed the best classification results with 86% sensitivity by using two features (RMS and range). Barth *et al*. [53] employed three classifiers, including boosting with decision stump, LDA and SVM, to measure gait patterns in PD to distinguish mild and severe gait impairment. The system was able to classify PDs and controls with 88% sensitivity and 86% specificity using the LDA classifier based on three activities—namely 10 m walking, heel-toe tapping, and foot circling. It reached a 100% sensitivity and specificity to distinguish mild from severe using optimal features—namely step duration, entropy, variance, energy ratio, and a

0.5–3 Hz energy band. Klucken *et al*. [54] used 694 features and three pattern recognition algorithms (LDA, AdaBoost, and SVM) to categorize patients in different stages. The developed eGaIT system, which consists of accelerometers and gyroscopes attached to shoes, was able to successfully distinguish patients from controls with an overall classification rate of 81%. The classification accuracy increased to 91% for more severe motor impairment or H&Y III patients.

Besides evaluating classifier, other works provided a complete motor assessment by analyzing the severity of several PD motor symptoms. Zwartjes *et al*. [55] used DTC to analyze motor activity and the severity of tremor, bradykinesia, and hypokinesia in patients with PD at three different levels of deep brain stimulation (DBS) treatment. An overall accuracy of 99.3% was achieved. Tzallas *et al*. [56] developed a system called PERFORM, using four accelerometers at each extremity and one accelerometer/gyroscope on the waist, to evaluate and quantify various symptom severity. The severity and type of tremor were classified by HMM classifier based on several time and frequency domain characteristics with 87% accuracy and 0.008 mean absolute error (*MBE*). The C4.5 DCT algorithm was used for LID detection and severity classification with an accuracy of 85.4% and a *MBE* of 0.31. A SVM classifier with optimum features (including approximate entropy, across correlation value, and range value) achieved 74.5% accuracy and 0.25 *MBE* for bradykinesia assessment. The detection of FoG was realized by an RFs classifier using the boot strap technique with 79% accuracy and 0.79 *MBE*. The PERFORM system also included a local base unit and a centralized hospital unit, allowing for the continuous remote monitoring and management of patients with PD.

2.3.2. Smartphone-based solutions

Given that smartphones are ubiquitous and have advanced built-in inertial sensors, research has recently sought to develop smartphone-based systems for PD assessments, which can keep the patient "connected" to his physician on a daily basis. The important features of existing smartphone-based solutions are summarized and compared in **Table 4**.

Arti cle	Sensors (Placement)	Features	Algorithm	Performance	Validity
57	Accelerometer (undisclosed)	Mean, SD[1], 25th percentile, 75th percentile, IQR[2], median, mode, range, skewness, kurtosis, mean squared energy, entropy, cross correlation, mutual information, cross entropy, DFA[3], instantaneous changes in energy, auto-regression coefficient, zero-crossing rate, dominant frequency component, radial distance, polar angle, azimuth angle.	RFs	Discriminate patients with PD from controls with an average *SE* of 98.5% and average *SP* of 97.5%.	Cross validation

Article	Sensors (Placement)	Features	Algorithm	Performance	Validity
8	Accelerometer & gyroscope & touch screen & microphone	Average frequencies, RMS angular velocity, speed of movement, amplitude of dominant rhythm, CV[4], PSD, RMS values.	SVM, RFs	94.5% (*AC*), > 0.85 (AUC)	Cross validation
58	Accelerometer (hips)	Freeze index, energy, cadency variation, the ratio of the derivative of the energy.	fuzzy Logic algorithm	89% (*SE*), 97% (*SP*)	Undisclosed
60	Accelerometer & gyroscope (hand)	Magnitude of acceleration and rotational velocity, SD of acceleration, mean magnitude of rotation rate.	BagDT	82% (*AC* in patients), 90% (*AC* in controls)	Cross validation
59	Accelerometer & gyroscope (ankle, trouser pocket, waist, chest pocket)	Mean, variance, SD, entropy, energy, Fi, power, RMS, interquantile range, kurtosis, frequency domain features.	AdaBoost. M1,	86% & 84% & 81% (*SE* at the waist, in the trouser pocket and at the ankle, respectively).	Cross validation
61	Accelerometer (hand or ankle)	Hand tremor: power between 4–6 Hz, fraction of power, power ration in 3.5–15 Hz to 0.15–3.5 Hz, total power from 0–20 Hz, peak power, average acceleration.Gait: average gait cycle, average stride length, average walking speed, average acceleration, the number of steps and the speed of turning 360°.	SVM	77% & 82% (*SE* & *AC* for hand resting tremor detection), 89% & 81% (*SE* & *AC* for gait difficulty detection).	Cross-validation

[1]SD-Standard Deviation;
[2]IQR-Inter-quartile range;
[3]DFA-Extent of randomness;
[4]CV-Coefficient of variation.

Table 4. Smartphone-based solutions for Parkinson's disease.

These smartphone-based solutions use the signal from the integrated accelerometers or gyroscopes in consumer-grade smartphones and in conjunction with machine learning

algorithms to quantify key movement severity symptoms (i.e., bradykinesia, FoG, hand tremor) and discriminate patients with PD from controls. Arora *et al*. [57] using an RFs classifier with a range of different time and frequency features of the acceleration time series, achieved 98.5% average sensitivity and 97.5% average specificity in differentiating patients with PD from controls. Another study by Printy *et al*. [8] developed an iPhone application using embedded hardware of a smartphone, including gyroscope, accelerometer, capacitive touch screen, microphone, and the front-facing camera, and a SVM algorithm to discriminate between more severe and less severe bradykinesia with an accuracy of 94.5%. The accurate classification of bradykinesia severity was not achieved in this work.

Some studies, on the other hand, aimed to detect FoG, a common motor impairment to suffer an inability to walk in PD patients. Pepa *et al*. [58] presented a smartphone-integrated accelerometer-based system to detect the FoG. They developed a linguistic fuzzy modelling (LFM) with Mamdani rule structure by fusing the information of freeze index, energy sum, cadency variation, and energy derivative ratio with a sensitivity of 89% and a specificity of 97%. In the smartphone-based system for FoG detection proposed by Kim *et al*. [59], data are derived from both embedded accelerometer and gyroscope. An AdaBoost.M1 classifier using several time and frequency domain features showed the best sensitivity of 86% at the waist, 84% and 81% in the trouser pocket and at the ankle, respectively.

Two other studies used the smartphone to measure the hand tremor symptom. Kostikis *et al*. [60] utilized a Breiman's RFs to classify upper limb tremor and achieved 82% accuracy in patients with PD and 90% accuracy in controls, with 0.9435 AUC. The feature metrics were derived from the acceleration vector and rotational velocity vector when patients performed two MDS-UPDRS postures—namely "Extended" and "Rest". Pan *et al*. [61] designed a prototype mobile cloud-based mHealth app on the Android platform called "PD Dr" to measure the severity of both hand resting tremor and gait difficulty, using the built-in accelerometer. The SVM classifier was used with a sensitivity of 77% and a specificity of 82% for hand resting tremor detection, and 89% sensitivity and 81% specificity in gait difficulty detection. Lasso regression approach was built to estimate the symptom severity. There was a strong correlation with PD disease stage (r=0.81), hand resting tremor severity(r=0.74), and gait difficulty severity (r=0.79).

2.3.3. Limitations and challenges

Given the relatively small number of classifier-based studies in this area and the wide variety of research questions addressed, ranging from activity classification to different symptom severity level assessment, it is currently difficult to address which classifier is ideal in PD populations for mHealth. Meanwhile, the accuracy levels of the classifiers were generalized on small sample sizes ranging from 5 to 27 subjects [50–53, 55–61]. Only one out of these studies enlisted a relatively larger sample of 92 patients with PD and 81 controls [54]. It is therefore important to evaluate the performance of classifiers according to larger, homogeneous population sets. Moreover, It is difficult to evaluate how effective or well performing of a classifier, because its performance also depends on the selected features and the properties of

wearable sensors (i.e., resolution, noise level). Therefore, the effectiveness of wearable inertial-based methods in mHealth regimens still has to be further examined.

Using a smartphone for PD management seems promising in mHealth, yet there are the same issues as those in smartphone-based fall detection systems. The performance and usability of smartphone-based solutions remain limited by the relatively lower quality of embedded sensors, and the limited battery life of smartphones, as well as the need to wear the smartphone in a fixed position.

Only very few studies provided a complete overall assessment of PD [55, 56]. Most of the existing solutions with external wearables sensors or the smartphones built-in sensors have limited focus on a particular motor symptom, and lack the important characteristic for PD-monitoring services, such as long-term recording, qualitative and quantitative assessments. Therefore, more effort should be put into providing a complete tool that comprises the most common PD motor disabilities, such as tremor, bradykinesia, LID, and FoG.

3. Wearable solutions for cardiac monitoring

Heart disease, a worldwide chronic condition, is the leading cause of death in many countries. There are various parameters that capture the characteristics of cardiac activity. Among them, resting HR is one of the simplest, yet most informative, cardiovascular parameters. Heart rate variability (HRV) has been identified as a prognostic marker for cardiac abnormalities. Although the "gold standard" for assessing cardiac abnormalities remains a 12-lead Holter, a large number of innovative and versatile wearable devices, including chest strips, wrist-worn devices, earphones, and smart clothing, have emerged as alternatives, which can provide the opportunity for prolonged, continuous cardiac rhythm tracking in real-world environments. Today, several portable devices are commercially available for determining cardiac status via a single-lead ECG, either by wearing a patch for continuous rhythm tracking [5] or using a smartphone for rhythm capture whenever needed. If multiple leads are needed to increase the accuracy of arrhythmia diagnosis, there are smart shirts that allow for 3- to 12-lead ECG monitoring [2].

3.2.1. ECG patch monitor

An ECG patch monitor (EPM) attached to the skin on the chest via an adhesive carrier generally consists of electrodes, a signal-processing subsystem, and a wireless data transmission subsystem. The two most representative examples of single-lead EPM are the Zio Patch recorder [62] and NUVANT PiiX event recorder [63].

The Zio Patch can be categorized as a single-lead Holter with a memory of up to 14 days of stored rhythms. The Zio Patch has a frequency response of 0.15–34 Hz, an input impedance greater than 3 MΩ, a differential range of ± 1.65 mV, and a resolution of 10 bits. There is a button on the patch allowing the patient to mark a symptomatic episode. Once the recording period is complete, the patient mails the patch back to iRhythm Clinical Centers (iCC), where

the recorded ECG data will be processed and analyzed by the Zio ECG Utilization Service (ZEUS) system with the capability of detecting up to 10 categories of rhythms. Rosenberg *et al.* [64] compared the Zio Patch with a 24-h Holter monitor in 74 consecutive patients. The mean wear time was 10.8 ± 2.8 days. Compared with the first 24 h of monitoring, there was an excellent agreement between the Zio Patch and Holter in identifying atrial fibrillation (AF) events. In another study, Turakhia *et al.* [65] evaluated the performance of the Zio Patch in 26,751 consecutive patients. The Zio Patch was well tolerated, with a mean monitoring period of 7.6 ± 3.6 days, and the median analyzable time was achieved 99% of the total wear time. The overall diagnostic yield of the Zio Patch was 62.2% for any arrhythmia and 9.7% for any symptomatic arrhythmia.

The NUVANT system consists of a 15-cm adhesive patch named the PiiX, a wireless data transmitter called zLink® and a patient trigger magnet [66]. The PiiX sensor samples the ECG signal at 200 Hz with a resolution of 10 bits. The PiiX patch that is integrated with multiple sensors cannot only continuously monitor many physiological parameters, including HR, HRV, RR, fluid status, body position, activity, and body temperature, but also automatically identify nonlethal cardiac arrhythmias [67], including bradycardia ≤40 bpm, pause ≥3 seconds, atrial fibrillation, ventricular tachycardia or ventricular fibrillation, tachycardia HR >130 bpm, a-Fib/a-Flutter (all rates), heart block, and fall-associated arrhythmia. When an arrhythmia is detected, the PiiX sends the data to zLink via Bluetooth. The zLink then transmits the data to the monitoring center or a caregiver using cellular communication. The clinical experience of the NUVANT/PiiX is currently lacking. One study with regard to patient compliance of the NUVANT system has shown no reduction in the on-patient longevity or performance of the device [66].

The ECG patch capable of recording up to three lead signals is on its way for the public's use [69]. A three-lead PEM, developed by IMEC and the Holst Center [70], integrates an ultra-low power ECG chip and a Bluetooth Low Energy (BLE) ratio, allowed to run continuously for 1 month on a 200 mAh Li-Po battery. The IMEC patch can monitor not only three channels ECG, but also the contact impedance, providing real-time information on the sensor contact quality that is important for aiding in filtering motion artifacts. The recording data are processed and analyzed locally on ECG SoC to reduce motion artifacts using adaptive filtering or principal component analysis and compute beat-to-beat HR based on discrete or continuous wavelet transforms.

PEM is considered to be a promising technology for its unobtrusive, wireless, and long-term recording capabilities. Further studies are necessary to examine the sensitivity and specificity of the recordings and long-term impact of the use of EPM in AF.

3.2.2. Smartphone-based monitor

Recently, a flood of smartphone-based monitors has been designed for heart rhythm monitoring, which falls into two broad categories, namely smartphone-only and smartphone with external sensors.

The most representative in the smartphone-only category is the camera-based apps, which measure the cardiovascular blood volume pulse (BVP) generated by repeated, rhythmic heart contractions (that can be registered by photoplethysmogram (PPG)) using the embedded camera in the smartphone. Researchers have shown that pulse rhythm and phase information regarding the BVP waveform can be deduced from the brightness change in the red (R), green (G), or blue (B) channels [68]. Several approaches to deal with the motion artifacts in the camera signals have been proposed to improve the measurement accuracy. The MIT laboratory used the blind source separation (BSS) to separate RGB color channels into independent components, which demonstrated its ability to extract the HR with digital, off-the-shelf webcams in normal ambient lighting in the presence of a limited range of motion artifacts [71, 72] Fang *et al*. [73] uncovered the underlying PPG signal from a single-channel recording using the dynamic embedding technique followed by ICA. This method relies only on the inherent temporal dynamic of the single-channel signal, making it suitable for all kinds of cameras. Thus, the built-in camera in smartphones could easily double as a heart rate monitor. Camera-based apps were subsequently brought into being based on these methods. Azumio's Instant Heart Rate app [74] is one of the most popular health apps on the market, which uses the smartphone's built-in camera and flash to compute HR and update the number through placing the tip of one's finger on the camera for about 10 sec. Many apps with advanced algorithms have also been launched for noncontact measurement of heart and respiration rate, such as a Vital Signs Camera app developed by Philips Innovation [75], extracting HR from the changes in color of the face and RR from the motion of the chest.

On the other hand, some external sensors, wired or wirelessly connecting with a smartphone, are used for sensing cardiac signals. These sensors transmit raw data to the smartphone for processing and analyzing based on computational algorithms embedded on smartphones. One example of these significant achievements is the most recent FDA approved AliveCor Heart Monitor platform [76], which supports both iPhone and Android platforms. It has been designed as a smartphone case with finger electrodes that snaps onto the back of a smartphone to measure the single-channel ECG and wirelessly communicate with the app on the phone. With secure storage in the cloud, the data can be retrieved confidentially by users themselves or their physician anytime, anywhere.

Documented clinical outcomes in the scientific literature with smartphone-based monitors is lacking at present. More work still needs to be done to examine the accuracy and sensitivity of the smartphone-based monitors.

4. Wearable solutions for other physiological parameters

There are no satisfactory wearable solutions that can provide continuous, stable, and reliable measurements for blood pressure and blood glucose at this stage [77]. Standard technology to monitor blood pressure requires an inflatable cuff to be pressurized, which may not suitable for continuous monitoring. Several approaches have been proposed for cuffless blood pressure measurement, such as arterial tonometry [78], measuring blood pressure over the radial artery

by placing a pressure transducer on the wrist to capture the radial pulse waveform, or indirectly estimating blood pressure from pulse wave transit time (PTT) [79–81]. However, their consistency and reliability are still under investigation compared to the conventional method.

Currently, glucose-level measurements usually require a blood sample via the finger-pricking method. The so-called "minimally-invasive" approaches, using a disposable biosensor needle inserted under the skin on the abdomen to derive the glucose level in interstitial fluid, have been developed for continuous blood glucose monitoring. The invasiveness currently required is a high barrier to realize a practical wearable device. Many efforts targeted the field of noninvasive glucose-monitoring (NGM) techniques have been reported. Many NGM approaches—namely reverse iontophoresis [82], impedance spectroscopy [83], electromagnetic sensing [84, 85], optical methods [86–90], and photoacoustic spectroscopy [91]—have been proposed. However, key challenges to apply these technologies to wearable blood glucose monitoring are the inherent lack of specificity behind these technologies, interference from other tissue components, and poor signal to noise ratio. Other studies have aimed to develop a glucose sensor on a contact lens to monitor the glucose level in tear fluid [92–96]. Google Inc. and the University of Washington have announced a prototype of "smart" contact lenses embedded with a fully integrated sensor with signal processing circuits and a wireless coil [96]. A drawback of this technique is the glucose concentration in tears is on the sub-mm level that is almost 10 times lower than the glucose concentration in blood. A microfabricated amperometric glucose sensor, prepared by immobilizing glucose oxidase (GOx) in a titania sol-gel layer [95], can enhance sensitivity at the same level as a glucose sensor can do directly in blood.

5. Summary

The wearable technologies highlighted in this chapter can improve the accessibility and convenience of healthcare by bringing clinic and hospital quality monitoring to the point of need. The greatest potential of the continuous and ubiquitous monitoring with wearables might be in enhancing our understanding of the evolving process of poorly defined chronic conditions and allowing for more personalized or precise treatment. However, the performance and usability of current technologies and systems according to larger, homogeneous population sets are currently lacking. The high-quality clinical evidence for the use of wearable systems in mHealth to improve chronic disease management and inpatient care is very limited. Future research should be aimed at high-quality clinical evidence related to the usability, accuracy, and robustness of wearable technologies. In addition, there are still many technical issues and limitations yet to be resolved to realize high robustness and reliability in long-term recordings. These include the lack of a full range of appropriate sensors, susceptibility to motion artifacts, battery life, lack of interoperability, security and privacy issues in data communication, the low reliability and poor specificity of cuffless blood pressure and noninvasive blood glucose-monitoring methods. Despite all the potential hurdles, we envision that there will be further evolvement and improvement in this field in the upcoming years.

Author details

Fang Zhao[1*], Meng Li[1] and Joe Z. Tsien[1,2]

*Address all correspondence to: fzhao@augusta.edu

1 Brain and Behavior Discovery Institute and Department of Neurology, Medical College of Georgia, Augusta University, Augusta, Georgia, USA

2 Banna Biomedical Research Institute, Xi-Shuang-Ban-Na Prefecture, Yunnan Province, China

References

[1] Di Rienzo M., Rizzo F., Parati G., Brambilla G., Ferratini M., Castiglioni P. MagIC system: a new textile-based wearable device for biological signal monitoring applicability in daily life and clinical setting. In: Conference Proceedings IEEE Engineering in Medicine and Biology Society; 2005; Shanghai, China. IEEE; 2005. p. 7167–7169. DOI: 10.1109/IEMBS.2005.1616161.

[2] Lee Y.D., Chung W.Y. Wireless sensor network based wearable smart shirt for ubiquitous health and activity monitoring. Sensor Actuat. B-Chem. 2009;140(2):390–395. DOI: 10.1016/j.snb.2009.04.040.

[3] Jakicic J.M., Winters C., Lagally K., Ho J., Robertson R.J., Wing, R.R. The accuracy of the TriTrac-R3D accelerometer to estimate energy expenditure. Med. Sci. Sports Exerc. 1999;31(5):747–754. DOI: 00005768-199905000-00020.

[4] del Rosario M.B., Redmond S.J., Lovell N.H. Tracking the evolution of smartphone sensing for monitoring human movement. Sensors. 2015;15:18901–18933. DOI: 10.3390/s150818901.

[5] Lobodzinski S.S. ECG patch monitors for assessment of cardiac rhythm abnormalities. Prog. Cardiovasc. Dis. 2013;56(2):224–229. DOI: 10.1016/j.pcad.2013.08.006.

[6] Mellone S., Tacconi C., Schwickert L., Klenk J., Becker C., Chiari L. Smartphone-based solutions for fall detection and prevention: the FARSEEING approach. Z. Gerontol. Geriatr. 2012;45(8):722–727. DOI: 10.1007/s00391-012-0404-5.

[7] Attal F., Mohammed S., Dedabrishvili M., Chamroukhi F., Oukhellou L., Amirat Y. Physical human activity recognition using wearable sensors. Sensors. 2015;15(12): 31314–31338. DOI: 10.3390/s151229858.

[8] Printy B.P., Renken L.M., Herrmann J.P., Lee I., Johnson B., Knight E., et al. Smartphone application for classification of motor impairment severity in Parkinson's disease. In: 36th Annual International Conference Proceedings of the IEEE Engineering in Medi-

cine and Biology Society (EMBC); 26–30 Aug. 2014; Chicago, IL, USA. IEEE; 2014. p. 2686–2689. DOI: 10.1109/EMBC.2014.6944176.

[9]   Elliott S., Painter J., Hudson, S. Living alone and fall risk factors in community-dwelling middle age and older adults. J. Community Health. 2009;34:301–310. DOI: 10.1007/s10900-009-9125-x.

[10] Hobert M.A., Maetzler W., Aminian K., Chiari L. Technical and clinical view on ambulatory assessment in Parkinson's disease. Acta Neurol. Scand. 2014;130(3):139–147. DOI: 10.1111/ane.12248.

[11] Topol E.J. Transforming medicine via digital innovation. Sci. Transl. Med. 2010;2(16): 16cm4. DOI: 10.1126/scitranslmed.3000484.

[12] Bouten C.V., Koekkoek K.T., Verduin M., Kodde R., Janssen J.D. A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity. IEEE Trans. Biomed. Eng. 1997;44(3):136–147. DOI: 10.1109/10.554760.

[13] Najafi B., Aminian K., Loew F., Blanc Y., Robert P.A. Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly. IEEE Trans. Biomed. Eng. 2002;49(8):843–851. DOI: 10.1109/TBME.2002.800763.

[14] Steins D., Dawes H., Esser P., Collett J. Wearable accelerometry-based technology capable of assessing functional activities in neurological populations in community settings: a systematic review. J. Neuroeng. Rehabil. 2014;11:36. DOI: 10.1186/1743-0003-11-36.

[15] Karantonis D.M., Narayanan M.R., Mathie M., Lovell N.H., Celler B.G. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. IEEE Trans. Inf. Technol. Biomed. 2006;10(1):156–167. DOI: 10.1109/TITB.2005.856864.

[16] Mathie M.J., Coster A.C., Lovell N.H., Celler B.G., Lord S.R., Tiedemann A. A pilot study of long-term monitoring of human movements in the home using accelerometry. J. Telemed. Telecare. 2004;10(3):144–151. DOI: 10.1258/135763304323070788.

[17] Bao L., Intille S. Activity recognition from user-annotated acceleration data. In: Pervasive Computing. 2004;3001:1–17.

[18] Huan L., Lei, Y. Toward integrating feature selection algorithms for classification and clustering. IEEE Trans. Knowl. Data Eng. 2005;17:491–502. DOI: 10.1109/TKDE.2005.66.

[19] Bianchi F., Redmond S.J., Narayanan M.R., Cerutti S., Celler B.G., Lovell N.H. Falls event detection using triaxial accelerometry and barometric pressure measurement. In: In Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 3–6 September 2009; MN, USA; 2009. p. 6111–6114. DOI: 10.1109/IEMBS.2009.5334922.

[20] Qiang L., Stankovic J.A., Hanson M.A., Barth A.T., Lach J., Gang Z. Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information. In: In Proceedings of the Sixth International Workshop on Wearable and Implantable Body Sensor Networks; 3–5 June 2009; Berkeley, CA, USA; 2009. p. 138–143. DOI: 10.1109/BSN.2009.46.

[21] Dadashi F., Mariani B., Rochat S., Büla C., Santos-Eggimann B., Aminian K. Gait and foot clearance parameters obtained using shoe-worn inertial sensors in a large-population sample of older adults. Sensors. 2014;14(1):443–457. DOI: 10.3390/s140100443.

[22] Pogorelc B., Gams M. Detecting gait-related health problems of the elderly using multidimensional dynamic time warping approach with semantic attributes. Multimed. Tools Appl. 2013;66:95–114. DOI: 10.1007/s11042-013-1473-1.

[23] Sposaro, F., Tyson, G. iFall: an android application for fall monitoring and response. In: Proceedings of the Annual International Conference of the IEEE on Engineering in Medicine and Biology Society (EMBC); 3–6 September 2009; Minneapolis, MN, USA. IEEE; 2009. p. 6119–6122. DOI: 10.1109/IEMBS.2009.5334912.

[24] Dai J., Bai X., Yang Z., Shen Z., Xuan D. Mobile phone-based pervasive fall detection. Pers. Ubiquitous Comput. 2010;14(7):633–643. DOI: 10.1007/s00779-010-0292-x.

[25] Yavuz G., Kocak M., Ergun G., Alemdar H., Yalcin H., Incel, O.D., et al. A smartphone based fall detector with online location support. In: In Proceedings of the International Workshop on Sensing for App Phones; 2 November 2010; Zurich, Switzerland; 2010. p. 31–35.

[26] Zhao Z., Chen Y., Liu J. Fall detecting and alarming based on mobile phone. In: In Proceedings of the 7th International Conference on Ubiquitous Intelligence & Computing and 7th International Conference on Autonomic & Trusted Computing (UIC/ATC); 26–29 October 2010; Shanxi, China; 2010. p. 494–497. DOI: 10.1109/UIC-ATC.2010.44.

[27] Fahmi P., Viet V., Deok-Jai C. Semi-supervised fall detection algorithm using fall indicators in smartphone. In: In Proceedings of the 6th International Conference on Ubiquitous Information Management and Communication; 20–22 February 2012; Kuala Lumpur, Malaysia. 2012. DOI: 10.1145/2184751.2184890.

[28] He Y., Li Y. Physical activity recognition utilizing the built-in kinematic sensors of a smartphone. Int. J. Distrib. Sens. Netw. 2013; 2013, p. 1–10. DOI: 10.1155/2013/481580.

[29] Majumder A.J.A., Rahman F., Zerin I., Ebel W., Jr., Ahamed S.I. iPrevention: towards a novel real-time smartphone-based fall prevention system. In: In Proceedings of the 28th Annual ACM Symposium on Applied Computing; 18–22 March 2013; Coimbra, Portugal; 2013. p. 513–518. DOI: 10.1145/2480362.2480462.

[30] Dai J., Bai X., Yang Z., Shen Z., Xuan D. PerFallD: a pervasive fall detection system using mobile phones. In: In Proceedings of the 8th IEEE International Conference on

Pervasive Computing and Communications Workshops (PERCOM Workshops); 29 March–2 April 2010; Mannheim, Germany. IEEE; 2010. p. 292–297. DOI: 10.1109/PERCOMW.2010.5470652.

[31] Lee R.Y., Carlisle A.J. Detection of falls using accelerometers and mobile phone technology. Age Ageing. 2011;40(6):690–696. DOI: 10.1093/ageing/afr050.

[32] Cao Y., Yang Y., Liu W. E-FallD: A fall detection system using android-based smartphone. In: In Proceedings of the 9th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD); 29–31 May 2012; Sichuan, China. IEEE; 2012. p. 1509–1513. DOI: 10.1109/FSKD.2012.6234271.

[33] Fang S.-H., Liang Y.-C., Chiu K.-M. Developing a mobile phone-based fall detection system on android platform. In: In Proceedings of the Computing, Communications and Applications Conference (ComComAp); 11–13 January 2012; Hong Kong, China. IEEE; 2012. p. 143–146. DOI: 10.1109/ComComAp.2012.6154019.

[34] Viet V.Q., Lee G., Choi D. Fall detection based on movement and smart phone technology. In: In Proceedings of the IEEE RIVF International Conference on Computing and Communication Technologies, Research, Innovation, and Vision for the Future (RIVF); 27 February–1 March 2012; Ho Chi Minh City, Vietnam. IEEE; 2012. p. 1–4. DOI: 10.1109/rivf.2012.6169847.

[35] Mehner S., Klauck R., Koenig H. Location-independent fall detection with smartphone. In: In Proceedings of the 6th International Conference on PErvasive Technologies Related to Assistive Environments; 28–31 May 2013; Rhodes, Greece. 2013. DOI: 10.1145/2504335.2504346.

[36] Koshmak G.A., Linden M., Loutfi A. Evaluation of the android-based fall detection system with physiological data monitoring. In: In Proceedings of the 35th Annual International Conference of the IEEE on Engineering in Medicine and Biology Society (EMBC); 3–7 July 2013; Osaka, Japan. IEEE; 2013. p. 1164–1168. DOI: 10.1109/EMBC.2013.6609713.

[37] Kau L.J., CHen C.S. A smart phone-based pocket fall accident detection, positioning, and rescue system. IEEE J. Biomed. Health Inform. 2014;19(1):44–56. DOI: 10.1109/JBHI.2014.2328593.

[38] Suryadevara V.K., Rizkalla M. Smartphone based fall detection and logic testing application using android SDK. J. Biomed. Sci. Eng. 2015;8(9):616–624. DOI: 10.4236/jbise.2015.89057.

[39] Viet V., Choi D.J. Fall detection with smart phone sensor. In: In Proceedings of the 3rd International Conference on Internet (ICONI); 15–19 December 2011; Sepang, Malaysia; 2011. p. 27-31.

[40] Shi Y., Shi Y., Wang X. Fall detection on mobile phones using features from a five-phase model. In: In Proceedings of the 9th International Conference on Ubiquitous Intelligence & Computing and 9th International Conference on Autonomic & Trusted

Computing (UIC/ATC); 4–7 September 2012; Fukuoka, Japan. IEEE; 2012. p. 951–956. DOI: 10.1109/UIC-ATC.2012.100.

[41] Zhao Z., Chen Y., Wang S., Chen Z. FallAlarm: smart phone based fall detecting and positioning system. Procedia Comput. Sci. 2012;10:617–624. DOI: FallAlarm: Smart Phone Based Fall Detecting and Positioning System.

[42] Kansiz A.O., Guvensan M.A., Turkmen H.I. Selection of time-domain features for fall detection based on supervised learning. In: In Proceedings of the World Congress on Engineering and Computer Science; 23–25 October 2013; San Francisco, CA, USA; 2013.

[43] Medrano C., Plaza I., Igual R., Sánchez Á., Castro M. The effect of personalization on smartphone-based fall detectors. Sensor. 2016;16(1):E117. DOI: 10.3390/s16010117.

[44] Abbate S., Avvenuti M., Bonatesta F., Cola G., Corsini P., Vecchio A. A smartphone-based fall detection system. Pervasive Mobile Comput. 2012;8(6):883–899. DOI: 10.1016/j.pmcj.2012.08.003.

[45] Habib M., Mohktar M., Kamaruzzaman S., Lim K., Pin T., Ibrahim F. Smartphone-based solutions for fall detection and prevention: challenges and open issues. Sensors. 2014;14(4):7181–7208. DOI: 10.3390/s140407181.

[46] Goetz C.G., Stebbins G.T., Wolff D., DeLeeuw W., Bronte-Stewart H., Elble R., et al. Testing objective measures of motor impairment in early Parkinson's disease: feasibility study of an at-home testing device. Mov. Disord. 2009;24(4):551–556. DOI: 10.1002/mds.22379.

[47] Dijkstra B., Kamsma Y.P., Zijlstra W. Detection of gait and postures using a miniaturized triaxial accelerometer-based system: accuracy in patients with mild to moderate Parkinson's disease. Arch. Phys. Med. Rehabil. 2010;91(8):1272–1277. DOI: 10.1016/j.apmr.2010.05.004.

[48] Moore S.T., MacDougall H.G., Ondo W.G. Ambulatory monitoring of freezing of gait in Parkinson's disease. J Neurosci Methods. 2008;167(2):340–348.

[49] Bächlin M., Roggen D., Plotnik M., Hausdorff J.M., Giladi N., Tröster G. Online detection of freezing of gait in Parkinson's disease patients: a performance characterization. In: Proceedings of the 4th International Conference on Body; Brussels, Belgium; 2009. p. 693–698. DOI: 10.4108/ICST.BODYNETS2009.5852.

[50] Salarian A., Russmann H., Vingerhoets F.J.G., Burkhard P.R., Aminian K. Ambulatory monitoring of physical activities in patients with Parkinson's disease. IEEE Trans. Biomed. Eng. 2007;54(12):2296–2299. DOI: 10.1109/TBME.2007.896591.

[51] Mazilu S., Blanke U., Hardegge M., Tröster G., Gazit E., Dorfman M., et al. GaitAssist: a wearable assistant for gait training and rehabilitation in Parkinson's disease. 2014 IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops); 24–28 March 2014; Budapest. IEEE; 2014. p. 135–137. DOI: 10.1109/PerComW.2014.6815179.

[52] Cancela J., Pansera M., Arredondo M.T., Estrada J.J., Pastorino M., Pastor-Sanz L. A comprehensive motor symptom monitoring and management system: the bradykinesia case. In: In Proceeding of the 32nd Annual Conference of the IEEE Engineering; 31 Aug 2010–4 Sept 2010; Buenos Aires. IEEE; 2010. p. 1008–1011.

[53] Barth J., Klucken J., Kugler P., Kammerer T., Steidl R., Winkler J., et al. Biometric and mobile gait analysis for early diagnosis and therapy monitoring in Parkinson's disease. In: In Proceedings of the 33rd Annual Conference of the IEEE Engineering in Medicine and Biology Society; 30 Aug 2011–3 Sept 2011; Boston, MA, USA. IEEE; 2011. p. 868–871. DOI: 10.1109/IEMBS.2011.6090226.

[54] Klucken J., Barth J., Kugler P., Schlachetzki J., Henze T., Marxreiter F., et al. Unbiased and mobile gait analysis detects motor impairment in Parkinson's disease. PLoS One. 2013;8(2):e56956. DOI: 10.1371/journal.pone.0056956.

[55] Zwartjes D.G.M., Heida T., van Vugt J.P.P., Geelen J.A.G., Veltink P.H. Ambulatory monitoring of activities and motor symptoms in Parkinson's disease. IEEE Trans. Biomed. Eng. 2010;57(11):2778–2786. DOI: 10.1109/TBME.2010.2049573.

[56] Tzallas A.T., Tsipouras M.G., Rigas G., Tsalikakis D.G., Karvounis E.C., Chondrogiorgi M. PERFORM: a system for monitoring, assessment and management of patients with Parkinson's disease. Sensor. 2014;14(11):21329–21357. DOI: 10.3390/s141121329.

[57] Arora S., Venkataraman V., Donohue S., Biglan K.M., Dorsey E.R., Little M.A. High accuracy discrimination of Parkinson's disease participants from healthy controls using smartphones. In: 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP); 4–9 May 2014; Florence. IEEE; 2014. p. 3641–3644. DOI: 10.1109/ICASSP.2014.6854280.

[58] Pepa L., Ciabattoni L., Verdini F., Capecci M., Ceravolo M.G. Smartphone based fuzzy logic freezing of gait detection in Parkinson's disease. In: 2014 IEEE/ASME 10th International Conference on Mechatronic and Embedded Systems and Applications (MESA); 10–12 Sept 2014; Senigallia. IEEE; 2014. p. 1–6. DOI: 10.1109/MESA.2014.6935630.

[59] Kim H., Lee H.J., Lee W., Kwon S., Kim S.K., Jeon H.S., et al. Unconstrained detection of freezing of Gait in Parkinson's disease patients using smartphone. In: 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 25–29 Aug. 2015; Milan. IEEE; 2015. p. 3751–3754. DOI: 10.1109/EMBC.2015.7319209.

[60] KostikisN., Hristu-Varsakelis D., Arnaoutoglou M., Kotsavasiloglou C. A smartphone-based tool for assessing Parkinsonian hand tremor. IEEE Trans. Biomed. Eng. 2015;19(6):1835–1842. DOI: 10.1109/JBHI.2015.2471093.

[61] Pan D., Dhall R., Lieberman A., Petitti D.B. A mobile cloud-based Parkinson's disease assessment system for home-based monitoring. JMIR Mhealth Uhealth. 2015;3(1):e29. DOI: 10.2196/mhealth.3956.

[62] iRhythm. Available from: http://www.irhythmtech.com/ [Accessed: Mar. 2016].

[63] Corventis [Internet]. Available from: http://www.corventis.com/ [Accessed: Mar. 2016].

[64] Rosenberg M.A., Samuel M., Thosani A., Zimetbaum P.J. Use of a noninvasive continuous monitoring device in the management of atrial fibrillation: a pilot study. Pacing Clin. Electrophysiol. 2012;36(3):328–333. DOI: 10.1111/pace.12053.

[65] Turakhia M.P., Hoang D.D., Zimetbaum P., Miller J.D., Froelicher V.F., Kumar U.N., et al. Diagnostic utility of a novel leadless arrhythmia monitoring device. Am. J. Cardiol. 2013;112(4):520–524. DOI: 10.1016/j.amjcard.2013.04.017.

[66] Engel J.M., Chakravarthy N., Katra R.P., Mazar S., Libbus I., Chavan A. Estimation of patient compliance in application of adherent mobile cardiac telemetry device. In: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 30 Aug 2011–3 Sept 2011; Boston, MA, USA. IEEE; 2011. p. 1536–1539. DOI: 10.1109/IEMBS.2011.6090448.

[67] Higgins S.L. A novel patch for heart rhythm monitoring: is the Holter monitor obsolete? Future Cardiol. 2013;9(3):325–333. DOI: 10.2217/fca.13.13.

[68] Verkruysse W., Svaasand L.O., Nelson J.S. Remote plethysmographic imaging using ambient light. Opt. Express. 2008;16(26):21434–21435.

[69] Lobodzinski S.S., Laks M.M. New devices for very long-term ECG monitoring. Cardiol. J. 2012;19(2):210–214.

[70] Imec. [Updated: Mar. 2016]. Available from: www2.imec.be.

[71] Poh M.Z., McDuff D.J., Picard R.W. Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. Opt Express. 2010;18(10): 10762–10774. DOI: 10.1364/OE.18.010762.

[72] Poh M.Z., McDuff D.J., Picard R.W. Advancements in noncontact, multiparameter physiological measurements using a webcam. IEEE Trans. Biomed. Eng. 2011;58(1):7–11. DOI: 10.1109/TBME.2010.2086456.

[73] Zhao F., Li M., Qian Y., Tsien J.Z. Remote measurements of heart and respiration rates for telemedicine. PLoS One. 2013;8(10):e71384. DOI: 10.1371/journal.pone.0071384.

[74] Azumio. Instant Heart Rate [Internet]. Available from: http://www.azumio.com/apps/heart-rate/ [Accessed: Mar. 2016].

[75] Philips. VitalSigns Camera [Internet]. Available from: http://www.vitalsignscamera.com/ [Accessed: Mar. 2016].

[76] AliveCor. Available from: http://www.alivecor.com/home [Accessed: Mar. 2016].

[77] Zhao F., Li M., Tsien J.Z. Technology platforms for remote monitoring of vital signs in the new era of telemedicine. Expert Rev. Med. Devices. 2015;12(4):411–429. DOI: 10.1586/17434440.2015.1050957.

[78] Tensys Medical. TL-300 [Internet]. Available from: http://tensysmedical.com/us/products/.

[79] Eeftinck Schattenkerk D.W., van Lieshout J.J., van den Meiracker A.H., Wesseling K.R., Blanc S., Wieling W., et al. Nexfin noninvasive continuous blood pressure validated against Riva-Rocci/Korotkoff. Am. J. Hypertens. 2009;22(4):378–383. DOI: 10.1038/ajh.2008.368.

[80] Garnier R.P., van der Spoel A.G., Sibarani-Ponsen R., Markhorst D.G., Boer C. Level of agreement between Nexfin non-invasive arterial pressure with invasive arterial pressure measurements in children. Br. J. Anaesth. 2012;109(4):609–615. DOI: 10.1093/bja/aes295.

[81] Saugel B., Meidert A.S., Hapfelmeier A., Eyer F., Schmid R.M., Huber W. Non- invasive continuous arterial pressure measurement based on radial artery tonometry in the intensive care unit: a method comparison study using the T- Line TL-200pro device. Br. J. Anaesth. 2013;111(2):185–190. DOI: 10.1093/bja/aet025.

[82] Leboulanger B., Guy R.H., Delgado-Charro M.B. Non-invasive monitoring of phenytoin by reverse iontophoresis. Eur. J. Pharm. Sci. 2004;22(5):427–433.

[83] Tao D., Adler A. In Vivo Blood Characterization From Bioimpedance Spectroscopy of Blood Pooling . IEEE Trans. Instrum. Meas. 2009;58(11):3831-3838. DOI: 10.1109/TIM.2009.2020836.

[84] Caduff A., Talary M.S., Mueller M., Dewarrat F., Klisic J., Donath M., et al. Non-invasive glucose monitoring in patients with Type 1 diabetes: a multisensor system combining sensors for dielectric and optical characterisation of skin. Biosens. Bioelectron. 2009;24(9):2778–2784. DOI: 10.1016/j.bios.2009.02.001.

[85] Tura A., Sbrignadello S., Cianciavicchia D., Pacini G., Ravazzani P. A low frequency electromagnetic sensor for indirect measurement of glucose concentration: in vitro experiments in different conductive solutions. Sensors. 2010;10(6):5346–5358. DOI: 10.3390/s100605346.

[86] Arnold M.A., Small G.W. Noninvasive glucose sensing. Anal. Chem. 2005;77(17):5429–5439.

[87] Vonlilienfeldtoal H., Weidenmuller M., Xhelaj A., Mantele W. A novel approach to non-invasive glucose measurement by mid-infrared spectroscopy: the combination of quantum cascade lasers (QCL) and photoacoustic detection. Vib. Spectrosc. 2005;38(1–2):209–215. DOI: 10.1016/j.vibspec.2005.02.025.

[88] Ellis D.I., Goodacre R. Metabolic fingerprinting in disease diagnosis: biomedical applications of infrared and Raman spectroscopy. Analyst. 2006;131(8):875–885.

[89]   Larin K.V., Eledrisi M.S., Motamedi M., Esenaliev R.O. Noninvasive blood glucose monitoring with optical coherence tomography: a pilot study in human subjects. Diabetes Care. 2002;25(12):2263–2267.

[90]   Malik B.H., Coté G.L. Real-time, closed-loop dual-wavelength optical polarimetry for glucose monitoring. J. Biomed. Opt. 2010;15(1):017002. DOI: 10.1117/1.3290819.

[91]   Lee S., Nayak V., Dodds J., Pishko M., Smith N.B. Glucose measurements with sensors and ultrasound. Ultrasound Med. Biol. 2005;31(7):971–977.

[92]   March W.F., Mueller A., Herbrechtsmeier P. Clinical trial of a noninvasive contact lens glucose sensor. Diabetes Technol. Ther. 2004;6(6):782–789.

[93]   Alexeev V.L., Das S., Finegold D.N., Asher S.A. Photonic crystal glucose-sensing material for noninvasive monitoring of glucose in tear fluid. Clin. Chem. 2004;50(12): 2353–2360.

[94]   Yao H., Shum A.J., Cowan M., Lähdesmäki I., Parviz B.A. A contact lens with embedded sensor for monitoring tear glucose level. Biosens. Bioelectron. 2011;26(7):3290–3296. DOI: 10.1016/j.bios.2010.12.042.

[95]   Patel J.N., Gray B.L., Kaminska B., Gates B.D. Flexible three-dimensional electrochemical glucose sensor with improved sensitivity realized in hybrid polymer microelectromechanical systems technique. J. Diabetes Sci. Technol. 2011;5(5):1036–1043.

[96]   Liao Y.T., Yao H., Lingley A., Parviz B., Otis B.P. A 3- \mu \hbox CMOS glucose sensor for wireless contact-lens tear glucose monitoring. IEEE J. Solid-St. Circ. 2012;47(1):335–344. DOI: 10.1109/JSSC.2011.2170633.

[97]   Tacconi C., Mellone S., Chiari L. Smartphone-based applications for investigating falls and mobility. In: In Proceedings of the 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth); 23–26 May 2011; Dublin, Ireland; 2011. p. 258–261.

[98]   Bai Y.W., Wu S.C., Tsai C.L. Design and implementation of a fall monitor system by using a 3-axis accelerometer in a smart phone. IEEE Trans. Consum. Electron. 2012;58(4):1269–1275. DOI: 10.1109/TCE.2012.6414995.

[99]   Hsieh S.L., Su M.H., Liu L.F., Jiang W.W. A finite state machine-based fall detection mechanism on smartphones. In: In Proceedings of the 9th International Conference on Ubiquitous Intelligence & Computing and 9th International Conference on Autonomic & Trusted Computing (UIC/ATC); 4–7 September 2012; Fukuoka, Japan. IEEE; 2012. p. 735–739. DOI: 10.1109/UIC-ATC.2012.153.

[100] Bai Y.W., Wu S.C., Yu C.H. Recognition of direction of fall by smartphone. In: In Proceedings of the 26th Annual IEEE Canadian Conference on Electrical and Computer Engineering (CCECE); 5–8 May 2013; Regina, SK, Canada. IEEE; 2013. p. 1–6. DOI: 10.1109/CCECE.2013.6567781.