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Wearable motion sensors to continuously measure real-world physical activities

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Purpose of review

Rehabilitation for sensorimotor impairments aims to improve daily activities, walking, exercise, and motor skills. Monitoring of practice and measuring outcomes, however, is usually restricted to laboratory-based procedures and self-reports. Mobile health devices may reverse these confounders of daily care and research trials.

Recent findings

Wearable, wireless motion sensor data, analyzed by activity pattern-recognition algorithms, can describe the type, quantity, and quality of mobility-related activities in the community. Data transmission from the sensors to a cell phone and the Internet enable continuous monitoring. Remote access to laboratory quality data about walking speed, duration and distance, gait asymmetry and smoothness of movements, as well as cycling, exercise, and skills practice, opens new opportunities to engage patients in progressive, personalized therapies with feedback about the performance. Clinical trial designs will be able to include remote verification of the integrity of complex physical interventions and compliance with practice, as well as capture repeated, ecologically sound, ratio scale outcome measures.

Summary

Given the progressively falling cost of miniaturized wearable gyroscopes, accelerometers, and other physiologic sensors, as well as inexpensive data transmission, sensing systems may become as ubiquitous as cell phones for healthcare. Neurorehabilitation can develop these mobile health platforms for daily care and clinical trials to improve exercise and fitness, skills learning, and physical functioning.

Keywords

accelerometer, activity monitor, gyroscope, mobile health, outcome assessment, physical activity, signal processing, stroke rehabilitation, telemedicine

INTRODUCTION

Mobile health or mHealth is a growing endeavor to improve healthcare services via mobile communication devices [1■■]. The cell phone enables continuous access to the Internet over broadband and Wi-Fi for data transmission of physiologic variables, physical activity, blood tests, images, social interactions, mental states, and environmental conditions [2■■]. By simultaneously assessing behavioral, physiological, and psychological states in the real world and in real time, mHealth also aims to quantify the states of health and well being. Feedback, cues, and updated instructions via graphics and text messages can be provided in real time based on the flow of information from and back to a patient. The result will be high-throughput, multistreamed, longitudinal datasets to facilitate disease prevention, diagnostics, compliance, personalized management, and behavioral change [3]. A global aim is to use this technology to reduce healthcare disparities, especially for patients with chronic diseases, and lower the long-term cost of more personalized care. This long-term management capability is especially important in neurologic rehabilitation after disabling spinal cord and traumatic brain injury, as well as in stroke, multiple sclerosis, and any progressive or neurodegenerative disease. Thus, the rehabilitation team may find remarkable opportunities in mHealth, just as it has for other assistive technologies.

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KEY POINTS

- Wireless inertial and motion sensor devices, worn on the arms, trunk, or legs, can send raw data over the Internet to reveal daily activities.
- Sensor-derived, activity pattern-recognition algorithms are being developed to identify the type, quantity, and aspects of quality of purposeful movements.
- Data about walking speed, distance, duration, and gait asymmetry, as well as exercise, can be used to provide remote feedback about practice and skills learning in the context of the home and community, as well as for ratio scale outcome measures.
- Future improvements in access to rehabilitation care at low cost may be made feasible by the combination of wireless broadband networks, ubiquitous penetration of cell phones, and wearable technologies for personal and environmental sensing.

Mobile health smartphone applications take advantage of external sensors and the camera, microphone, global positioning satellite (GPS), and accelerometer built into these communication devices. The phone already serves as a transmission relay for Bluetooth-equipped weight scales, blood pressure and heart rate devices, equipment for exercise, and mental and social health state assessments. Bio-monitoring of blood chemistries, embedded lab-on-a-chip sensors, and tele-monitoring for remote personal health advice by professionals are moving forward as well. Evidence for efficacy is growing, if slowly [4]. For example, the first mHealth Cochrane analysis of randomized clinical trials (RCTs) for self-management of type 2 diabetes found larger effects on glucose and hemoglobin A1c control for cell-phone-based interventions compared with conventional information and computer use [5]. Studies of efficacy, however, are sparse. Across all health conditions at the end of 2012, 176 RCTs of mHealth technologies were listed at clinicaltrials.gov [6], but few have been published or relate to neurologic disability.

This review describes the efforts to bring wearable, wireless sensor networks to bear on community-based assessments and treatments to improve walking, exercise, fitness, and other mobility-related activities after neurologic injuries and diseases. It addresses the challenge of a White Paper [7] from the National Institute of Child Health and Human Development, which concluded 'Advanced technology/sensors must be developed to establish better tracking of compliance and clinical outcomes, at several International Classification of Functioning, Disability, and Health levels. New, low-cost, portable sensors may ultimately replace prevailing clinical instruments used for outcome assessments'. Inexpensive smartphones and tablets are lowering the complexity of this challenge as they can communicate with multiple sensors placed on the body; initiate, store, or transmit data for processing; provide a variety of user interfaces; download instructions and reminders; and remotely update applications.

SENSOR PLATFORMS

A wide range of wearable sensors are available commercially that provide the raw data to describe arm, trunk, and lower extremity actions outside of a motion analysis gait laboratory [8]:

(1) Triaxial accelerometer: accelerations/decelerations, velocity, and displacement of a body segment in x, y, and z axes.
(2) Gyroscope: angular velocity and rotation.
(3) GPS signal: location primarily outdoors, may calculate speed and distance of continuous walking with smartphone applications.
(4) Magnetometer: directional vectors of spatial orientation.
(5) Electromyography (EMG): dry electrodes for surface EMG of timing and amount of muscle group activation.
(6) Goniometer: joint angular range of motion.
(7) Resistive flex and pressure sensing: fiberoptic or deformable textile across a joint detects angular change; piezo electrode for distribution of weight on sole to define stance in the gait cycle.
(8) Environmental context: ambient sound, light, motion-activated photo or video.

The choice of sensors, number, and placement will depend on the activity and movement variables to be ascertained. Practical sensor systems must meet many complex design requirements, from cosmetic, privacy, and technology acceptability by users to signal processing, data transmission, annotation, and scalability for easy use (see list below). Especially important for motion sensing is the accuracy and speed of feature detection and classifier algorithms that turn a sequence of inertial signals into a recognizable movement pattern to measure clinically important details of gait and other purposeful activities. Technical features for practical remote motion-sensing systems include:

(1) Sensors:
   (a) type, number, and position depend on specific body metrics sought;

   (b) design – for example, piezoelectric or capacitive microelectro-mechanical system accelerometer;
   (c) cosmetic acceptability, ease and reproducibility of placement;
   (d) raw signal structure and sensitivity to events;
   (e) firmware instructions for device components;
   (f) partial data processing on sensor chip.
(2) Platforms:
   (a) interoperability by using common software, communication, data processing, and confidentiality protocols;
   (b) open source, publically available standards;
   (c) end-to-end system reliability.
(3) Data transmission:
   (a) choice of wireless standards – Bluetooth, Zigbee, Wi-Fi, voice channels, short message service, and Universal Mobile telecommunications Systems;
   (b) cost;
   (c) frequency of data sampling;
   (d) bandwidth;
   (e) power consumption and energy source;
   (f) reliability;
   (g) data time stamping;
   (h) error check;
   (i) storage capacity;
   (j) secure data at each stage of collection, transfer, and storage.
(4) Signal processing:
   (a) temporally fuse data synchronously from multiple sensors and body sites;
   (b) analytic algorithms:
      (i) features assessed include mean of signal, peak frequency, correlation of axis, signal energy, and standard deviation;
      (ii) classifier models include naïve Bayes, support vector machine, decision tree, hidden Markov, neural networks, spectrum analysis, and random forest;
      (iii) integrate multiple layers of the classifier, for example, activity, context, and sensor location;
      (iv) artifact recognition and examine outliers;
   (c) environmental context of activity;
   (d) speed of processing;
   (e) machine-learning analysis.
(5) Resolution of data:
   (a) software to interpret data from sensors and other sources of information to provide new insights into health states;
   (b) normalized for matched population and sensitive to individual's daily functioning over time;
   (c) discern trajectory of change and clinically meaningful gains and declines;
   (d) visualize data using customizable tools and reports.
(6) Annotation:
   (a) describe changes in health, mood, behavior, social circumstances, and environment;
   (b) ontological encoding of data across studies, for example, Unified Medical Language System for standard description of medical condition, treatments, responses, and contexts.
(7) Methods to scale up applications:
   (a) simplify instructions, minimize time and effort by user, and keep cognitive load low;
   (b) minimize the steps and increase automaticity in data flow during acquisition, processing, analysis, and search;
   (c) conceptualize summary data for practical uses, such as feedback, monitoring, and outcome tools.
(8) Data accessibility in common databases:
   (a) NIH or Research Electronic Data Capture (REDCap) databases;
   (b) annotated raw data repository for data mining.
(9) Data privacy and security:
   (a) encryption;
   (b) Health Insurance Portability and Accountability Act requirements.

Commercial devices

Recently, fitness, exercise, and wellness gadgets have come to the social networking market. Can they be used for patient care? In general, these cosmetically striking devices detect successive movements by a single biaxial or triaxial accelerometer placed in a pocket or on a wristband (e.g., FitBit, BodyMedia, and FuelBand). Results are summarized by downloading the data to a computer or smartphone usually via Bluetooth. Episodic and cyclical body movements are then calculated as activity or step counts or converted into calorie counts. Each swing of the arm or forward propulsion of the trunk is interpreted as a stride during repetitive exercise. Actions with low gravitational force or unusual combinations of acceleration–deceleration of short duration may be misinterpreted, however. Adventitious movements may be interpreted as the motion of interest. Reliability and validity are uncertain in healthy persons in real-world settings and are yet to be studied in disabled persons. At best, a wrist-worn accelerometer may distinguish being sedentary, household walking and running as distinct activities and correctly classify the intensity of activity 50% of the time [9]. In their present configuration, these are not suitable for research on patients with neurologic impairments.

Single accelerometer-based step counters have been available for 2 decades for outpatient use (e.g., Actigraph, Pensacola, Florida, USA; StepWatch Activity Monitor, Oklahoma City, Oklahoma, USA) [10,11]. Their count of steps over time generally correlates with the degree of walking impairment for patients with stroke (e.g., slower walkers take fewer steps) [12] and other neurological diseases. Like even less sophisticated pedometers, they may not detect all steps when the cadence falls below 50 per minute, walking speed slows below 0.6 m/s [13], or the gait pattern includes irregular movements. None measure walking speed or have yet been enabled to download to a smartphone. Triaxial accelerometer systems placed posteriorly at the midline of the waist use proprietary algorithms to detect the gait cycle and walking speed (e.g., Actibelt, Munchen, Germany), but so far tend to be less accurate in patients with greater impairment who walk slowly [14–16]. Indeed, multisensor systems are significantly more accurate than any of these single accelerometers to measure activity and estimate energy expenditure [16].

Research devices

An important goal for rehabilitation is to be able to remotely classify human activities and quantitatively measure the quality of their component movements outside of a motion analysis laboratory. Wireless gait laboratory systems (e.g., APDM, Portland, Oregon, USA) that integrate from two to seven accelerometers and gyroscopes worn on the wrists, ankles, and chest or waist, plus additional types of sensing, are said to be accurate for revealing the gait cycle and walking speed. Combinations of accelerometers are also sufficient to detect postural imbalance [17], and may help detect or predict falls. Wheelchair activity and energy consumption measurement also requires multiple sensors on each arm and the chair [18]. These systems, because of cost and complexities in the management, have primarily been used in controlled settings, but not for continuous community usage enabled by automatic downloading to a smartphone.

Comfortable, user-friendly sensor network designs compatible with the notion of mHealth are becoming available [19■■]. In one study, low-cost, miniaturized triaxial accelerometers with electronic circuits were placed over the tibia just above both ankles in healthy and hemiplegic participants. A template walk at several speeds for 10 m was used to help train the activity pattern-recognition algorithm for each individual [20]. The synchronous bilateral raw inertial signals were examined for features related to the timing of components of each stride, including heel-off, toe-off, peak swing, end of swing, and foot flat. A machine learning, Bayesian activity-recognition classifier was developed that grouped the activities and set the features that distinguished them. The algorithm then recognized subsequent bouts of walking across a day's activity and calculated walking speeds in the stroke patients as low as 0.1 m/s, along with distance and duration of each bout, and limb asymmetries in stance and swing times. This protocol led to high correlation with ground truth measures during walking in the community [20,21]. This sensor and analysis system was then used to provide feedback over the Internet about daily walking bouts in terms of speed, duration, and distance in a RCT during inpatient stroke rehabilitation at 15 sites in 12 countries [22]. Over 2100 h of activities were identified and quantified in 140 individuals, revealing the progression of walking-related measures and the actual amount of physical therapy provided for mobility. A Bluetooth connection from the sensors can download the data to a smartphone as well, then to a remote server for algorithm processing. Another research group placed bilateral accelerometers at mid-leg along with a gyroscope to try to eliminate the template walk, but their algorithm was only accurate when walking speed exceeded 0.6 m/s [23]. Other sensor placements and approaches to feature extraction from the accelerometer signal have been reported for subacute stroke [24], Parkinson's [25], and multiple sclerosis [17].

Thus, much progress is being made for personalized motion technologies. A smartphone with a continuously running software application that compresses and transmits the data to a central server can be an effective hub to manage multiple streams of sensor and other physiological data [26]. Practical sensing for the study of patients, however, requires technical and logistical development and planning [2■■]. In addition to the features listed above, cultural acceptance of technologies must evolve to optimize utilization. For widespread utilization, essential needs include interoperability of software and communication systems, publicly open standards, and qualitative and quantitative evidence about what works for what population under specified conditions [4,27]. For neurology and rehabilitation, efficacy and effectiveness trials are necessary before a final iteration of hardware, software, and infrastructure should be scaled for wide usage.

MOTION SENSING FOR DAILY CARE

Disabled persons, such as those after stroke, take far fewer steps daily, with fewer and shorter bouts of walking compared with healthy peers [28]. Critical research to understand how to reduce the risk factors for vascular disease, for example, and to reduce disability and increase daily participation will benefit from the ability to quantify the type, quantity, and quality of daily activities [8]. Sensor networks that monitor upper [29] and lower extremity [20] activities should facilitate accurate ongoing assessment during community functioning and enable frequent recommendations about how to progress exercise and skills practice from remotely located professionals. Sensors, then, may alter the behavior by offering feedback and personal activity auditing that encourages self-efficacy through the use of graphics and instruction from anywhere the Internet reaches. When particular exercises and skills practice are prescribed during long-term rehabilitation efforts, both patients and caregivers may benefit from remote supervision that addresses their concerns about safety and how best to work to advance the reacquisition of skills.

Although this level of monitoring could be viewed as an invasion of privacy, disabled persons are likely to applaud the accessibility of rehabilitation supervision in the context of their home and community at low cost. Tele-neurology [30] and tele-rehabilitation [31] could interface with wearable sensor technology to complement home-based care and compliance with the medical recommendations.

SENSORS FOR CLINICAL TRIALS

Having ground truth about activity levels, in terms of frequency, duration, intensity, and energy consumption, will turn the assumptions about the quantity of exercise and practice during trials into certainties. For example, all of the large recent RCTs of treadmill and robotic training to improve walking after stroke [12,32–34], spinal cord injury (SCI) [35,36], Parkinson's [37,38], and multiple sclerosis [39] have assigned individuals in the control and experimental groups to a specified number of hours of weekly treatment. None of the studies, however, can report with confidence how much walking and exercise occurred during planned practice sessions or whether participants practiced locomotor skills and exercised outside of formal training times [40]. Exercise trials that take place in the community are even less likely to be able to capture the quantity of practice [41,42]. Yet, a bias toward high or low levels of practice beyond what the investigative team sees may have a confounding impact on the effects of the experimental therapy. For example, participants who practice more may gain better skills; incorrect practice could reduce the effect of the formal therapy. The quantity and quality of an experimental physical intervention may also vary across the multiple sites of an RCT or change when a new therapist replaces the one who was trained at the onset of the trial. Good trial design recommends that extensive training in provision of a complex physical intervention take place before an RCT starts and that videotaping of the intervention or in-person, intermittent monitoring be part of the protocol at subsequent intervals. The conventional approach to these monitoring needs may be less reliable and cost more than intermittent remote sensor monitoring of actual practice (how much and how well) during formal training sessions and in between therapies.

Continuous monitoring of what individuals actually perform enables other benefits to trial integrity and design. Serial sensor measures can provide dose–response assessments or be used for imputation by statisticians when a participant drops out. Real-world sensing also offers ecologically sound, interval, and ratio scale assessments to augment questionnaires and ordinal scales about disability, participation in fulfilling personal goals and roles, and physical functioning (Table 1). Quality of life tools for this have become a requirement as primary or secondary outcomes in neurologic trials. Most diseases have their own tool, often derived from the questions developed for the Medical Outcomes Study's SF36 and now represented in the NIH's NeuroQOL toolbox [43]. These Likert-scaled measures of change in the daily physical activity and ratings of difficulty (climbing stairs, walking one block, etc.), however, have usually not been confirmed by the real-time studies of these activities. For example, the reported level of independence by persons with SCI differed from what clinicians found on testing [44]. Wearable sensors can provide that ground truth.

Just as self-reporting scales stand as a partial surrogate for actual activity and participation, so do other commonly used walking-related outcome tools, such as the timed short-distance walk (6–15 m) and the distance walked in 2–6 min in a laboratory setting. In general, improved effects on surrogates do not necessarily transfer into health benefits; indeed, the surrogate may fail as a guide to the most clinically meaningful and effective therapies [45]. In neurorehabilitation trials, a pretest to posttest gain of more than 20% in 10-m speed or 6-min distance often reaches statistical significance and favors one intervention over another. The

Table 1. Comparison of conventional scales and wireless, wearable sensor-derived tests of mobility-related functioning

Data	Usual method	mHEALTH sensors
Type of physical activity	Self-report diary or checklist; observe in laboratory; video; short distance timed walk or distance walked in 2–6 min.	Activity pattern-recognition algorithms; walk, cycle, leg exercises identifiable by sensor data processing
Quantity frequency/ duration	Observation; inertial movement/step counts if accelerations are high enough	Directly measure wave forms of individual components and whole actions
Quality	Laboratory motion analysis or pressure mat system	Compare each leg during step cycle in context of environs
Location of activity	Self-report; laboratory	Anywhere; global positioning and ambient context sensing for site identification
Reliability	Inter-rater; test–retest	Ground truth measurement vs. sensor-based algorithm
Validity	Content/construct for each scale	Face validity; responsiveness
Statistical testing	Ordinal scales of physical functioning	Interval/ratio scale data
Data entry	Computer	Smartphone, tablet
Human factors	Train examiners in test administration	Train participants in a culture of technology
Regulation	Local IRB and HIPAA	Local IRB and HIPAA, possibly Food and Drug Administration

HIPAA, Health Insurance Portability and Accountability Act; IRB, institutional review board.

clinical meaningfulness of such change, however, is uncertain. The gain may generally correlate with self-reported functional measurement tools [46], but outliers are common, because reliability of self-reports are uncertain. The ability to serially capture walking-related variables in the home and community, to examine changes in speed and leg symmetry on varied surfaces, and capture changes in exercise capacity, for example in relation to pain, fatigue, or adverse effects of medications, should provide greater insight into the effectiveness of new therapies in all patients for whom an evidence-based trial suggests efficacy [47,48].

The frequency at which patients might be monitored by wearable activity-sensing networks depends on the object of the study. Levels of walking activity using pedometers require about 7 days of data collection to obtain a stable and representative average for healthy persons [49] to as little as 2 days for those with incomplete SCI [50]. For a clinical trial of a walking intervention of 3 months' duration, a minimal dataset might include 2 weeks of daily monitoring prior to starting the comparison treatments, then for 1 week monthly or at the time of scheduled outcome measures. For a drug trial, activity might be measured continuously for at least a month – 2 weeks prior and at least 2 weeks after the initiation to detect fluctuations in response to medications (e.g., dyskinesias or freezing of gait in Parkinson's disease and leg spasms in SCI). Skills practice at home might be assessed for 1–2 sessions a week to monitor the quality of movements. Schedules for feedback about the performance to motivate compliance will have to be empirically derived.

CONCLUSION

Wireless remote sensing to monitor the type, quantity, and quality of physical activities, daily participation, and skill reacquisition offers great potential for neurologic and neurorehabilitation patient care and clinical trials. Progressive reductions in the cost, size, and energy requirements of gyroscopes, accelerometers, other physiologic sensors and data transmission over the Internet, along with empirical work on activity-recognition algorithms, suggest that wearable systems may become ubiquitous tools. Efficacy and effectiveness trials are necessary, however, before clinicians can utilize the sensor data for ecologically sound monitoring and outcome measures.

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Conflicts of interest

There are no conflicts of interest.

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