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NEUROREHABILITATION AND RECOVERY (J KRAKAUER AND T KITAGO, SECTION EDITORS)

Wearable Sensors to Monitor, Enable Feedback, and Measure Outcomes of Activity and Practice

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Abstract

Purpose of Review Measurements obtained during real-world activity by wearable motion sensors may contribute more naturalistic accounts of clinically meaningful changes in impairment, activity, and participation during neurologic rehabilitation, but obstacles persist. Here we review the basics of wearable sensors, the use of existing systems for neurological and rehabilitation applications and their limitations, and strategies for future use.

Recent Findings Commercial activity-recognition software and wearable motion sensors for community monitoring primarily calculate steps and sedentary time. Accuracy declines as walking speed slows below 0.8 m/s, less so if worn on the foot or ankle. Upper-extremity sensing is mostly limited to simple inertial activity counts. Research software and activity-recognition algorithms are beginning to provide ground truth about gait cycle variables and reveal purposeful arm actions. Increasingly, clinicians can incorporate inertial and other motion signals to monitor exercise, activities of daily living, and the practice of specific skills, as well as provide tailored feedback to encourage self-management of rehabilitation.

Summary Efforts are growing to create a compatible collection of clinically relevant sensor applications that capture the type, quantity, and quality of everyday activity and practice in known contexts. Such data would offer more ecologically sound measurement tools, while enabling clinicians to monitor and support remote physical therapies and behavioral modification when combined with telemedicine outreach.

Keywords Telemedicine · Rehabilitation · Outcome measures · Physical activity · Activity monitor · Self-management · Gait · Accelerometry

Introduction

For all neurological diseases, wearable sensors are twenty-first century tools that are increasingly used to try to improve diagnosis, treatment, compliance, personalized clinical management and feedback, and patient education [1•]. For daily care and research trials, sensors can enable continuous monitoring and clinically meaningful outcome measurements about physical activities such as strengthening and conditioning exercise, practice of degraded skills, and activities of daily living, so they are highly relevant to rehabilitation efforts [2, 3]. A variety of commercial and research sensor systems can be clipped to the chest, arm, waist, and leg, worn in a pocket or shoe or adhered to the skin. The combination of an accelerometer plus other motion sensors is called an inertial measurement unit or an IMU. Wearable IMUs have become ubiquitous monitors of step counts, exercise, and sleep in healthy persons. Big data analytic methods have enabled the accelerometer in smartphones to detect and classify differences in activity among large populations in relation to age, gender, weight, and disease states [4].

The most frequent application of wearable inertial sensing in neurology thus far is to measure and give general feedback to increase walking. More is on the near horizon. For neurological rehabilitation, mobile health (mHealth) applications of wearable IMUs outside of the clinic or laboratory offer the possibility of remote transmission of intermittent or continuous, high-fidelity, objective, patient-centered data during daily activities and practice. Upper- and lower-extremity accelerometer, gyroscope, and derived kinematic signals could be analyzed to provide sensitive measurements of the type,

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quantity, and quality of clinically important movements, potentially serving as a biomarker of gains and declines in function over time and after interventions. This real-world audit of activity and compliance may also offer clinically meaningful outcome measures in naturalistic settings, instead of only having self-reports about the type and amount of activity.

Ground truth about activity also provides a firm basis for feedback about exercise, skilled movements, and gait, allowing sensors to serve as part of a behavioral intervention technology [5••, 6••]. Wearables may be used in concert with telemedicine video interactions between users and therapists, which could lower the cost of rehabilitation care, as well as enable outreach to patients who have no access to rehabilitation expertise [7•]. Clinical trials of pharmacologic and neural repair interventions to date usually do not include a rehabilitation practice component. Sensors enable an inexpensive, standardized, remote rehabilitation effort to optimize the activity-dependent and task-related benefits of the experimental intervention [8]. In addition, remote testing becomes feasible, which may reduce the burdens on participants and give investigators serial data about important outcomes. For example, remote intermittent tests of functional capacity could take place in the home using a standard 15-m walking test or 6-min walk for endurance while wearing sensors.

This is the exciting promise. The reality must catch up. We review some of the basics about activity sensing that explain present limitations, the pros and cons about existing systems for neurological and rehabilitation applications, recent clinical trial results with sensing, and strategies for their near-term deployment.

Types of Wearable Wireless Sensors

Over 20 companies offer wearable sensors for clinical research; commercial fitness companies offer many models. Some of the key requirements of systems that might find their way into rehabilitation research include battery life, type of wireless transmission, capacity to form a network of sensors, ability to log data, availability of raw data signals to the investigator, standard activity-recognition algorithms, and support by software libraries such as MATLAB and Python [9, 10].

The most frequently deployed commercial sensors are wrist-worn triaxial accelerometers that measure accelerations from which velocity and displacement of a body segment in x, y, and z axes can be estimated. These commercial systems use proprietary algorithms that often depend on an inertial or rotational signal greater than a set threshold, which is then defined as an activity count, for example, for a step. Peak vertical center of mass displacements can also be recorded when the inertial sensor is worn at the low back or waist. However, analytic methods for step counts derived from wrist- and trunk-worn sensors become inaccurate when walking is slow and accelerations during leg swing are low and irregular, as in persons with hemiparetic gait [11••]. In practical terms, the peak acceleration and angular velocity of the leg occurs during the swing phase between toe-off and heel-strike in the gait cycle, which is most readily measured by a leg-worn device. When the sensor is placed on the top of the foot, an algorithm will be able to include a definite signal of no movement in mid-stance and will detect turns. A magnetometer may be added to assess directional vectors of spatial orientation. A barometric pressure sensor will recognize a change in altitude, even rising from sit to stand. The combination of an accelerometer with gyroscope and magnetometer is the most often deployed IMU. Thus, from any known body location, an investigator can obtain linear accelerations, angular velocities, and a heading angle with respect to magnetic north.

A global positioning satellite (GPS) signal is most accurate outdoors to provide location (context about activity) and calculate speed and distance of continuous walking with a wrist band and smartphone application. The subject must start and stop the app, however, to capture a continuous walk or the device may average standing with walking time. A heart rate monitor signal, usually from wrist plethysmography, is often fused with the inertial signal in commercial wrist sensors to give context about effort and metabolic information (aerobic effect, calories). For special requirements, wireless sensing can incorporate electrocardiogram, electroencephalogram, or electromyogram signals; a goniometer or other flexible material for joint movement angles; piezo-electrodes to measure, for example, foot pressure; biosensors such as continuous glucose monitors; and contextual information from light or ambient sound sensors. Sensor information can be supplemented and given context by smartphone-based, in-the-moment self-reports about mood, pain, social interaction, type of activity, or other personal events.

Unfortunately, no off-the-shelf system is available for rehabilitation studies in the community to collect, synchronize, and analyze upper-extremity actions or leg movements other than walking. Published studies often introduce home-grown algorithms to classify and measure movements in the laboratory. Most commercially available systems use proprietary analytic algorithms and the raw data often is not accessible, so an investigator cannot pursue either validation of the algorithm, debugging, or additional analyses [9, 12•], but this confounder is changing [13]. Given the growing interest in remote monitoring of activity in patients who participate in pharmacological trials for neurologic diseases, the next five years should bring more accurate, flexible, and relevant research systems within reach of clinical investigators. Table 1 shows some of the companies whose sensor systems allow access to raw accelerometer and other IMU data in relation to whether the data can be accessed remotely, which is necessary for feedback, and has been validated in patient populations.

Table 1 Sensor systems for research that allow access to raw data

Manufacturer	Configurations	What is measured	Access to raw sensor signal data (Y/N)	Remote data access (Y/N)	Studies validating measures in impaired neurologic population
Actigraph actigraphcorp.com	Wrist/hip worn	Activity count Energy Expenditure Steps Activity/sedentary Bouts Body position Total sleep time Heart rate R-R intervals	Yes Triaxial accelerometer, gyroscope, magnetometer, inclinometer, ambient light sensor	Yes, via a hub	Less than 80% accuracy at walking speed 1.2–0.8 m/s. (1)
ActivInsights activinsights.com	Wrist worn	Physical activity intensity Sleep/wake measures	Yes, for research-grade sensor Triaxial accelerometer, light, temperature	No	None identified
APDM apdm.com	Multiple body locations	Gait analysis Kinematics Physical activity level Balance Postural sway	Yes. Triaxial accelerometer, gyroscope, magnetometer	No, but pending	[39]
Axivity axivity.com	Logging sensor with accessories for wrist wear	MET Signal vector magnitude Wear time validation Sleep	Yes Triaxial accelerometer, light, temperature	No	[39]
Biosensics biosensics.com	Chest, wrist, leg	Gait analysis Kinematics Fall risk Postural sway	Yes Triaxial accelerometer	Yes for processed but not raw data Can store on sensor	None identified
Mc10 mc10inc.com	Adhesive wearable	Physical activity classification Stationary postural classification HR and variability Respiration rate Sleep metrics	Yes Triaxial accelerometer, gyroscope, biopotential	Yes, via a hub	None identified
MiniSun minisun.com	Chest, thighs, soles	Gait analysis Physical activity Energy expenditure Posture and transitional movements	Yes Biaxial accelerometer	No	For METS [46]
Moticon moticon.de	Shoe insole	Foot pressure Balance Force Ground contact time Direction of movement	Yes Triaxial accelerometer, pressure	Yes, live streaming to cloud storage	None identified
Shimmer shimmersensing.com	Any location	Determined by user	Yes Triaxial accelerometer, gyroscope, ECG, EMG, GSR	No	None identified

Common Measures Captured by Wearable Devices

The signals from well-placed wearable inertial sensors with reliable activity-recognition algorithms have quantified sitting down and standing up; walking; spatial-temporal gait variations; running; stair climbing; movement during sleep or a seizure, tremor, and truncal or limb ataxia; episodic movement disorders such as torticollis; wheelchair propelling; and upper-extremity activity counts. Identification of each activity, however, requires fusion of the signals from each body sensor. The choice of sensors, number, and placement depends on the activity and movement variables to be ascertained. Practical sensor systems must meet many complex design requirements, including cosmetic, privacy, and technology acceptability by users, as well as signal processing, data transmission, annotation, and scalability for easy use [9]. To date, no singular strategy has been adopted for sensor placement, data pre-processing, extraction of features from the inertial signal, and activity classification across key functional movements [14]. This poses the greatest limitation at present for routine use of sensing in clinical research and care.

Step Counting

Step counting is the most common function of commercial wearable activity trackers offered by Fitbit, Garmin, Jawbone, Apple, and others. Leonardo da Vinci would have found them to be more advanced than his invention of the first mechanical step counter, which was worn at the waist with gears rotated by a long lever arm tied to the thigh. Increasingly, companies such as FitBit (www.fitabase.com) provide some research support to remotely access and monitor the activity data from individual users. This service makes consumer-grade sensors a possible option for researchers looking for ready-to-use wearables to estimate sedentary time or to identify periods of continual walking activity at speeds > 0.8 m/s in persons without irregular gait pattern deviations [15]. Wrist-worn accelerometers, however, do not consistently count steps when the wrist is stationary, such as pushing a stroller or walker or using treadmill hand rails. They may record invalid steps when folding laundry, whisking or gesturing.

The accuracy of research-grade devices varies widely for impaired persons. For example, Treacy et al. examined patients who walked < 1.2 m/s but could walk at least 10 m during inpatient rehabilitation [11••]. The Fitbit One was worn on the ankle and wrist, the ActivPAL on the thigh, the G-Sensor on the hip, the Garmin Vivofit on the wrist, the Actigraph on the hip, and the StepWatch just above the ankle. Results for hemiparetic persons were best when the device was worn on the least affected leg. These systems do not allow investigators to simultaneously capture and merge signals from the hemiparetic and less-affected leg to assess bilateral movement deviations. Compared to automated GAITRite walking measurements, the ankle and thigh sensors were much more accurate as walking speed fell below 0.8 m/s. At < 0.4 m/s, the Fitbit One on the ankle began to drop from 90% down to 40% accuracy in counting steps, and the ActivPAL dropped from 70% to 43%. Only the StepWatch, for reasons noted later, maintained an accuracy of 90–100%. Thus, as the acceleration of leg swing decreases, devices became less accurate, but not as inaccurate as when worn on the wrist or hip. A sensor system, then, ought to be validated prior to a trial for its accuracy in detecting activity counts for the range of community walking speeds and levels of disability of the specific population.

The Food and Drug Administration cleared the StepWatch (Modus, Inc.) as a class 2 medical device for use in research. Its adaptable filtering and patient-specific calibration, based on several signature movements during stepping at one of the three levels of cadence, enable a more flexible algorithm that accounts for its better appreciation of a stride at slow walking velocity. Remarkably, its inertial IMU is a single-axis analog accelerometer (most other IMUs include a micro-electrical mechanical triaxial sensor). The company has released a platform that allows researchers to remotely access step count summary data, making it a viable option for more accurate, longitudinal tracking of patients with neurological conditions. Remote daily access to data is an important direction for companies. An example of this requirement for clinical trials occurred in the Locomotor Experience Applied Post-Stroke (LEAPS) trial [16]. For 400 participants who were asked to wear the ankle sensors for 5 days at baseline and at the end of the trial, adherence rates for the StepWatch 3 monitor for at least two days of wear were only 68% for the first day, 61% for the second, and 53% for both days. Of note, non-compliance was significantly associated with lower Fugl-Meyer score, slower walking speed, and poorer endurance. Adherence might have been better if daily activity counts had been uploaded and made available to the researchers, who would then have contacted non-compliers to find out whether the sensor was working properly or to resolve barriers to use.

Characteristics of Gait

Step counts in real-world settings in real time have been useful, but for persons with neurological impairments or undergoing rehabilitation, clinicians would especially value remote measures during community activities that include task-related variations in walking speed, stride length, gait cycle time, cadence, percent time in stance/swing and double/single-limb support, and kinematics. The Ambulatory Parkinson's Disease Monitoring (APDM) system is highly accurate over defined distances in a clinic. The system can report postural sway area, trunk range of motion, lower-limb gait cadence, stride length, velocity, gait cycle time, and postural transitions, as well as hip, knee, and ankle kinematics when using additional sensors. But the sensors must be in radio contact with a nearby computer. APDM is currently testing its system outside the lab setting in patients with a variety of neurological impairments. Other investigators report additional analytic strategies to capture walking speed and gait features [17–19•].

In addition, the standard machine learning pipeline for sensor-based movement assessment consisting of inertial signal pre-processing, feature extraction, and classifier training is increasingly being compared to deep learning frameworks for movement classification accuracy [20]. For example, disease or disability phenotypes were discerned by using sensor-derived gait parameters to distinguish among non-frail, pre-frail, and frail persons [21]. The key parameters obtained with shank sensors and derived by an artificial neural network analysis were propulsion duration and acceleration, heel-off and toe-off speed, mid-stance and mid-swing speed, and speed norms. Remote monitoring of the upper extremity (UE) may also need to incorporate more sophisticated analytic methods.

Heart Rate

During mobility activities and exercise, knowledge of an individual's heart rate (HR) enables an investigator to monitor exercise safety and provide feedback to gradually increase the intensity of exertion for a variety of health benefits in sedentary, disabled persons. Many commercial wrist monitors provide estimates of HR and energy expenditure, but HR data is usually not synchronized to gait data within research sensor systems. Indeed, HR accuracy from wrist sensors is less than expected, declines at higher heart rates, and leads to energy expenditure estimates that can exceed 25% median error rates [22•, 23]. In addition, no clinically meaningful important difference has been established for HR increases during overground walking during exercise in older disabled persons, so HR goals for hemi- and paraparetic persons are uncertain.

Applications Relevant to Neurorehabilitation

Risk Factor and Behavioral Management

Sensors can be deployed as a behavioral intervention technology, in which ground truth about activity and exercise enable goal-setting, instruction, or coaching on ways to meet goals, adherence to convenient practice schedules, barrier identification, and self-monitoring [9]. Tailored counseling plus remote supervision have been found to be critical components to increase practice and exercise. Heterogeneous motion-sensing trials that mostly deployed a smartphone, combined with behavioral interventions to reduce risk factors for stroke and cardiovascular disease (e.g., blood pressure, waist size, exercise level), have shown only modest evidence of efficacy [24••, 25•, 26]. The type and frequency of feedback, however, has not yet reached the levels supported by theories for self-efficacy [5••, 27].

Upper extremity

The 9 degrees of freedom of motion of the UE and the range of UE neurological impairments have been a challenge when aiming to discern purposeful movements outside of a lab or clinic. Even more difficult is to determine whether the hand successfully reached and grasped an object during free-ranging activities. The relative amount of use of a paretic limb compared to the non-paretic arm has been quantified along several motion-related variables [28•, 29]. Of note, self-reports about actual use of the UE during a clinical trial differed from the ground truth, with high variability in half of the 64 subjects; underreporting was most common [30•, 31]. Thus, self-reports about perception of use and actual use may differ and affect trial results. An interesting strategy was tested to recognize the arm movements used to perform the task of pouring a cup of tea. Investigators used a simple technique to recognize the occurrences of six predefined orientations of a triaxial wrist sensor. A similar technique might reveal measurements of basic movements to be practiced remotely when logged by the user and transmitted to a therapist [32]. A kinematic analysis of UE movements, enabled by multiple IMUs on the chest, scapula, and arm, could also help define purposeful, self-care actions. Recognition algorithms could be developed from movement templates obtained by studying perhaps six to eight key UE movements in hemiparetic persons with varying degrees of motor impairment, including forward reach to grasp and lifting the hand to the mouth or face within peri-personal space bounded by the width of the torso at levels from the waist to the top of the head. Additional sensors, however, would be necessary to detect a successful grasp or pinch of the hand. Deep learning strategies built upon data obtained from many hemiparetic persons might enable detection with high accuracy in the future.

The frequency, intensity, and laterality of activities performed by the upper extremities during wheelchair propulsion has been demonstrated in those with spinal cord injury using IMUs positioned on both wrists, on the chest, and on one wheel of the wheelchair [33]. Individualized calibration of moderate-vigorous physical activity was found to improve accuracy [34], as it has in other studies [7•].

Sensing Across Diseases

Stroke

A review of trials that deployed lower-extremity wearable sensors for persons with stroke found some evidence for improvement in activity and participation, but the designs and aims of the 11 studies with 550 participants had highly varied methods and outcome measures [35•]. During inpatient rehabilitation, lower-extremity sensors have been used to successfully monitor the intensity of walking therapy and provide feedback to try to increase the amount and velocity of walking practice. Results mostly revealed no added gains, perhaps due to time limitations for each therapy during inpatient rehabilitation [36–38].

Parkinson's Disease

A variety of studies reveal good clinimetric properties for assessing gait in persons with PD, including the detection of short stride and shuffling, but perhaps less so for freezing [39–41]. A phase 2 randomized clinical trial in 40 participants used two ankle or foot accelerometers and a smartphone to measure home and community gait speed, cadence, stride length, and leg symmetry in real time, along with auditory feedback and cueing to limit freezing of gait. Feasibility of feedback was demonstrated and balance improved in the feedback group [42].

Balance

A meta-analysis of seven small RCTs of IMU-based interventions for static or dynamic balance with feedback in adults with Parkinson's, stroke, and peripheral neuropathy and frail older adults found significant overall effects of training, especially for up to 36 sessions, on static steady-state balance and possibly several gait outcomes [43]. The APDM balance system has also shown promise in persons with a mild traumatic brain injury in detecting excessive sway [44].

Sleep Disorders

Sleep disorders are common in those with neurological disorders and may affect rehabilitation efforts. The most popular method of sleep quality assessment is based on measuring body acceleration patterns from wrist sensors. A chest sensor may improve appreciation of body positional changes and accelerations to estimate sleep parameters during polysomnography at home [45].

Telerehabilitation

Remote monitoring of outpatients over the Internet with personalized instruction about skills practice and exercise for strengthening and conditioning is made especially feasible by wearable sensing. The therapist can measure how well a patient actually performs specified practice tasks and routine activities. For clinical trials and care, this strategy expands the possibility of receiving more therapy at low cost [7•]. Several home-based compared to clinic-based interventions with interactive devices after stroke have been equivalent in enhancing gains after mild to moderate stroke, so sensors and telerehabilitation may also be able to deliver care in select patients that is at least as good as clinic visits.

Conclusions

For routine use in the rehabilitation of neurological diseases, a variety of IMU systems are available to monitor step counts and cadence outside the laboratory, but user-friendly solutions to gather data remotely about the type and quantity and quality of practice and of spontaneous gait or functional use of the upper extremity are just becoming available. The most flexible system for ease of use in research would include recommendations about the locations for sensors to be worn in relation to the tasks to be monitored; precise synchronization of data across all wireless sensors; continuous data collection capacity for > 8 h without a computer having to be within sensor transmission range; > 8 h of data storage on the IMUs or on a smartphone when real-time feedback is planned; open access to raw signals and to activity-recognition algorithms; analytic methods for upper- and lower-extremity activities that were proven accurate in disabled persons; automated standard outcome measurements along with methods to go deeper into assessments; flexible behavioral modification paradigms built into a system's software; and a common platform so that investigators can store sensor and metadata for others to use with privacy and permission protocols. As these tools become more robust, rehabilitation researchers will be able to broaden their strategies to enhance outcomes.

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Compliance with Ethical Standards

Conflict of Interest Bruce H. Dobkin and Clarisa Martinez each declare no potential conflicts of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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