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NEW HORIZONS IN SENSOR DEVELOPMENT

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Abstract

Background—Accelerometery and other sensing technologies are important tools for physical activity measurement. Engineering advances have allowed developers to transform clunky, uncomfortable, and conspicuous monitors into relatively small, ergonomic, and convenient research tools. New devices can be used to collect data on overall physical activity and in some cases posture, physiological state, and location, for many days or weeks from subjects during their everyday lives. In this review article, we identify emerging trends in several types of monitoring technologies and gaps in the current state of knowledge.

Best practices—The only certainty about the future of activity sensing technologies is that researchers must anticipate and plan for change. We propose a set of best practices that may accelerate adoption of new devices and increase the likelihood that data being collected and used today will be compatible with new datasets and methods likely to appear on the horizon.

Future directions—We describe several technology-driven trends, ranging from continued miniaturization of devices that provide gross summary information about activity levels and energy expenditure, to new devices that provide highly detailed information about the specific type, amount, and location of physical activity. Some devices will take advantage of consumer technologies, such as mobile phones, to detect and respond to physical activity in real time, creating new opportunities in measurement, remote compliance monitoring, data-driven discovery, and intervention.

Keywords

physical activity; context; measurement; intervention; mobile phone

INTRODUCTION

The ability to relate physical activity to health depends on its accurate measurement. Research to refine and improve techniques and instruments for measuring physical activity

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has been ongoing for years. Although substantial progress has been realized, none of the available methods is fully satisfactory because of problems related to cost, convenience, and measurement error. Technologies that can support collection of objective physical activity measures on a potentially massive scale, improve the accuracy and utility of the data, and allow unprecedented data sharing are here or on the near horizon. This paper describes emerging technologies, methods, and opportunities for advancing the field of objective physical activity measurement. Best practices are outlined to accelerate development of next-generation sensor technologies and maximize the value of ongoing research when those new technologies become available. We also identify gaps in knowledge where the field would benefit from additional device development. Finally, we make recommendations for three target audiences: engineers/device developers, measurement scientists/statisticians, and investigators who use these devices and methods in health and behavioral research.

This paper is intended to be a general introduction to emerging physical activity measurement technologies and to stimulate discussion about best practices and future directions. Though this overview cannot thoroughly discuss new methods, cite all relevant literature, or fully explain the rationale and implications of our recommendations, we hope it helps prepare the research community to make good use of future technologies.

CURRENT METHODS OF PHYSICAL ACTIVITY MEASUREMENT

The activity measurement community has expressed an interest in measuring nine concepts in physical activity measurement. We discuss current methods used to measure these concepts and the unique challenges that each present.

Energy Expenditure

The end goal of many studies is to estimate energy expenditure (EE), especially for obesity research. The limitations of using doubly-labeled water and indirect calorimetry for direct measurement, discussed by Freedson et al. in this supplement, have led to the development of methods that estimate energy expenditure from wearable physiological sensors that measure body/limb motion, heart rate, or other physiological variables.

Body and Limb Motion

Body motion can be used to estimate aspects of physical activity and sedentary behaviors, and devices and algorithms that attempt to do this by measuring hip or limb acceleration have proliferated (6). The size, convenience, and affordability of these devices will continue to improve as developers take advantage of low-cost, low-power, and extremely small 3-axis micro electro mechanical systems accelerometers, along with expanded memory and more capable microprocessors. Current devices can operate for months by saving summary measures, such as counts and vector magnitudes, but newer devices also will be capable of saving the raw, unfiltered acceleration pattern for extended periods of time. As devices add new capabilities, such as posture and specific behavior type detection, ensuring comparability between data collected from different devices is increasingly a concern.

Heart Rate

Heart rate monitors are used to measure exertion or improve motion-based estimation of energy expenditure, but they are limited as “stand alone” physical activity measures. Newer devices are embedded in fabric chest straps, but all existing and foreseeable devices are burdensome to wear for more than a few days. Devices for non-chest locations (e.g., ear, wrist, and finger) involve somewhat awkward positioning, and differentiating the heart rate signal from “noise” on a moving body is difficult to overcome (1).

Other Physiological and Chemical Indicators of Exertion

Physiological signals such as skin temperature, galvanic skin response, respiration rate, and foot pressure might be useful for improving physical activity or energy expenditure estimation when used with accelerometery or heart rate monitoring, and for monitoring wear time. Respiration is of interest to those studying exposure to environmental allergens and toxins, and some work is being done on chemical sensing, such as non-invasive glucose measurement. Each of these physiologic sensors, however, presents new challenges in terms of ergonomics, size, cost, battery life, and usability.

Pose or Limb Position

Pose, or the relative position of multiple limbs in three dimensions, might be valuable for detecting activities such as sitting, yoga, physical therapy exercises, and weight lifting. New accelerometers can measure static gravitational force and thus determine orientation. This information may be insufficient, however, to identify slow movements or specific poses, especially if sensors become displaced when worn. Gyroscopes in combination with accelerometers can be useful for assessing three-dimensional movements (19), notwithstanding battery life and calibration challenges. Room-based optical tagging and computer vision systems that detect limb position (23) might be useful in research using room calorimeters, but applications in field settings are limited.

Muscle Activation

Detecting muscle activation may prove especially valuable for understanding the impact of resistance activities on health. Although it may be possible to use accelerometers to detect posture and motion during strength training activities, reliably measuring body mass moved is likely to require new types of sensing. Machine learning and signal processing can be applied to analysis of electromyographic signals (14), but current methods require electrodes stuck to or even in the skin, which is not practical for extended field deployment.

Location and Proximity

Most efforts to understand the relationship between a person’s environment and physical activity level have used global positioning system (GPS) devices for acquiring location. Although GPS devices are being miniaturized and have improved battery life, they still do not always provide an identifiable location. They can take 15 minutes to lock onto satellite signals when someone exits a building, which could lead to loss of position data for short trips, and they typically do not work indoors. One challenge is that longitude and latitude coordinates are only an intermediate step in determining how people interact with, or are influenced by, their surroundings. Better-quality geographic information systems (GIS) databases linking location coordinates to the properties of those places are required.

Energy Consumption

Studying energy balance requires data not only on physical activity but also energy consumption. Use of mobile phones and their audiovisual processing capabilities can help people keep food diaries, respond to food frequency questionnaires, and achieve weight management goals. Active areas of research include use of automatically or semi-automatically processed images to infer information about food type and quantity (17). Even with these new tools, measuring eating patterns typically requires substantially more burdensome self-report than measurement of physical activity.

Other Self-report Information

For some interventions, self-reported activity or context about factors, such as perceived exertion, may be as critical as understanding the person’s actual movement. Devices that use electronic ecological momentary assessment and context-sensitive ecological momentary assessment (i.e., the device reacts based on a person's location and actions) may reduce subject burden by focusing question-asking at the most meaningful times (13). However, any self-report assessment has some inherent limitations.

Limitations of Current Measures and Methods

Strengths and weaknesses of monitors used to measure various aspects of physical activity have directly influenced which activities are most actively studied in laboratory and field settings.

Laboratory Testing—Lab tests permit the use of sensors under highly-controlled conditions. The most accurate yet burdensome sensors, such as indirect calorimeters or wired electrocardiogram monitors, can be worn only for a few hours at a time. Researchers with room calorimeters often run studies lasting a day or more, but limitations of current technologies have largely dictated shorter lab studies in which participants undergo scripted activities under artificial conditions. Some types of activities, such as structured exercises, are easily reproduced in the lab. Sedentary behavior as it occurs in free-living settings, however, is largely absent from these studies. Also underrepresented in these settings are resistance exercises, activities where the motion may be influenced by the environment (e.g., street cycling vs. riding a stationary cycle ergometer), and "multi-tasking" activities where people may switch between activities without reaching a physiological steady state. In many studies, participants wear a variety of devices so that performance of the various devices can be directly compared.

Field Testing—Many everyday activities, particularly the transition between activities within a day, are difficult to reproduce in the laboratory. Despite improvements, the cost of collecting and analyzing data from monitors is higher than from self-report, leading to challenges ranging from device cost to the burden of data cleaning and analysis. Consequently, in field studies participants typically wear sensors for a week or less, usually only during "waking hours," raising concerns about reactivity, sample bias, and the impact of non-wear time on activity levels (27). Most researchers do not simultaneously collect information about transportation mode, seasonal variability, and the influence of environmental factors, such as proximity to people or other devices, or special situations such as traffic. All of these factors can influence physical activity patterns.

EMERGING TECHNOLOGY AND METHODS

We expect to see a gradual improvement in overall device performance rather than the development of fundamentally new types of sensors in physical activity measurement devices. Breakthroughs will likely result from using multi-modal sensor fusion—combining data from several types of sensors, sometimes located on different parts of the body or in the environment—into a single system that is then used to infer precise, second-by-second detail about physical activity type, amount, and location. These changes, in turn, will create new opportunities in methods. New monitors should permit longer-term, lower-cost, higher-compliance deployments enabling a broader spectrum of physical activity concepts to be simultaneously measured in real-life settings.

Emerging Trends in Technology

Raw Data Processing—Devices will be capable of storing large amounts of raw data from each of several sensors for extended time periods. Although new devices may still output proprietary summary measures, such as counts, access to the raw data will facilitate use of well-defined, non-proprietary algorithms to summarize the activity observed. This, in turn, will facilitate cross-device comparison. In addition, it will be possible to use the data to not only estimate energy expenditure, but also compute ambulatory state and the specific type of activity.

Multiple Sensor Data Fusion—Access to raw sensor data from inexpensive sensors should help facilitate data fusion to improve physical activity measurement. Some devices will incorporate multiple sensors into their electronics, such as one accelerometer for high-sensitivity measurement of slow/light/sedentary motion and another for high-sensitivity measurement of moderate and vigorous motion. Others will permit researchers to gather data from multiple sensors that are time synchronized. Researchers should expect improved measurement capabilities from devices using sensor fusion, including more detailed and accurate information about activity type, device use/compliance, and environmental contexts such as location. For example, newer systems might combine information from GPS, motion, heart rate, infrared and ultraviolet light, direction, air pressure, and even ambient sound sensors to infer whether someone is indoors or outdoors—information any sensor alone cannot reliably provide. The system might also use multiple sensors to infer location and mode of transport (16).

Activity/Context Inference Using Statistical Pattern Recognition—New devices have sufficient computational power and memory to permit use of statistical pattern recognition algorithms that process raw data, often from multiple sensors, and infer detailed information about behavior or environmental contexts. For instance, features computed from raw sensor patterns can be used to infer specific activity type (4,15,22,29). Features also may encode periodicity of limb motion (computed using Fourier analysis), degree of limb synchronization (computed using correlation), or other information about sensor movement. Such features can be used to train pattern classification algorithms. Features computed from multiple sensors, perhaps located on the waist, upper limb, and lower limb, can be combined to improve behavior and context recognition (20). This is how emerging location systems combine multiple radio signals with databases of locations of cell towers and WiFi nodes, in addition to GPS, to infer location (12). This reduces lock times and allows the systems to work indoors. Similarly, knowing location information may help a device more accurately infer activity type. For example, incorporating the statistical knowledge that a “bench press” or “arm stretches” may be more likely to occur at a gym or home than at the supermarket, a device may improve its ability to detect those particular physical activity types by using location information. Sensor fusion from wearable devices can even be used for automatic detection of behaviors related to energy consumption, such as eating and chewing (2). When devices store raw, time-synchronized data, activity inference can be done after data collection or in real-time by devices that have sufficiently powerful processors such as found in most mobile phones.

A challenge will be establishing the validity of such techniques in field deployments, because most algorithms proposed so far have only been tested under controlled conditions. Although work is ongoing to develop person-independent algorithms for activity type detection and energy expenditure estimation, small amounts of training data from specific individuals will improve such models. The new multimedia capabilities of devices such as mobile phones will be used to simplify the process of collecting the required examples, making a task that may currently seem time-consuming and impractical, practical. Another consideration is that the inference algorithms do fail, although with sufficient training, data failure rates can be reduced. Statistical techniques that use the inferred activities as outcome variables may need to be adapted to account for the noise in the activity and context inference.

Wireless Data Exchange—Facilitating multiple data sensor fusion will be the emergence of devices with low-power wireless chips that enable precise time synchronization of multiple devices and transmission of real-time raw or summary data to a data collection device located on the body or elsewhere. For example, the use of synchronized, multiple limb information may permit more extensive activity inference than data from a single body position (3,29). Low-power wireless protocols may also provide new sensing capabilities. For instance, by detecting proximity to mobile phones with Bluetooth®, emerging devices may even be able to detect whether someone is likely to be near another person, such as a family member, providing new contextual information (25).

Personal Health Monitoring Devices—The emergence of personal health monitoring devices sold by consumer electronic companies, such as pedometers, accelerometers and heart rate monitors, which interface with phones, computers, and music players, will enable researchers to deploy sophisticated measurement devices at substantially lower costs than most of today's popular research monitors. Some of these companies will provide programmer interfaces to their devices, which will allow engineers to repurpose them for research needs. It is anticipated that some devices will be designed with open specifications so that, unlike existing commercial options, they can be modified and replicated inexpensively by researchers. These trends will be accelerated if the research community adopts standards for conducting cross-monitor validation tests, such as those proposed elsewhere in this supplement (7).

Compliance and Compliance Monitoring—Many measurement devices do not provide unambiguous data on subject device-use compliance. For instance, monitors may return zero values that appear to be due to lack of compliance even when people are actually wearing them properly but are completely sedentary, and GPS records do not differentiate when the device is not working versus when it could not find a signal. New devices will address these limitations, in part, by providing better compliance information using sensor fusion. For example, a skin temperature sensor in a device worn touching the skin, as in the SenseWear armband (Bodymedia Inc., Pittsburgh, PA) (26), might be used to detect device malfunction or that the device was removed.

In addition to providing better compliance data, new devices may help improve it. Some devices will be sufficiently small and waterproof so they can be worn 24 hours per day, reducing the need to remember to put them back on. Moreover, new algorithms may permit sensors to be worn on body locations other than the hip and, in some cases, under the clothing, increasing wear time and social acceptability. Some devices will continuously detect if they are being worn and used properly and provide real-time feedback to the subject about how to do so, which in turn should improve compliance.

Ubiquity of Mobile Phones—A major opportunity in physical activity measurement is being created not by a new class of sensor, but by the ubiquity of mobile phones with multiple sensors and capabilities already built in, including large memory storage, micro electro mechanical systems motion sensors, location sensing, low-power wireless networks, and fast processors. Most importantly, potential subjects will already own these sophisticated, sensor-enabled computers, and will be accustomed to carrying them nearly everywhere and keeping them charged, unlike devices handed out in research studies. The phone's built-in Internet access will permit remote data collection and study compliance monitoring. By leveraging this consumer investment in technology, and the massive engineering effort being devoted by the telecom industry to improve services such as location finding, researchers will have access to a "free" device that can be used for data storage, real-time activity detection, real-time compliance monitoring and encouragement, and novel forms of feedback for health interventions. As phones improve, physical activity measurement tools can be improved as well.

Some challenges to using mobile phones must be overcome. One is that the multiple uses of the phone will reduce researcher control over the device. Another is that the mobile phone market is fragmented, requiring systems to be developed on multiple operating systems. Finally, running CPU and sensor-intensive applications continuously could affect phone usability. Each of these challenges appears manageable, however.

Context-Sensitive Ecological Momentary Assessment for Self Report—Devices such as mobile phones that have an input/output mechanism and that can detect activity or context in real time permit context-sensitive ecological momentary assessment. That is, questions can be triggered in response to likely physical activity (or lack thereof) or proximity to a location or object of interest. Context-sensitive ecological momentary assessment may reduce the burden of self-report, especially because software applications can be designed in a fun and lighthearted way that encourages additional reporting and offsets the annoyance of interruption. Mobile phones using speech recognition for audio keyword spotting (11) might further simplify data input.

Advances in Web-Based GIS Mapping Systems—The longitude/latitude information provided by GPS is inadequate for understanding the relationship between physical activity and the environment. What is really needed is context information about the location, such as landmarks, roads, open spaces, or type of businesses that exist around a particular place. Researchers can expect to see an increasing number of mapping and GIS-related programmer interfaces that allow for mobile devices with wireless data network access to make real-time queries about what is at a particular location. These databases—particularly those that allow for community contributions and edits, such as walkability audits (5) conducted by community members using a data collection application on mobile phones or data contributed by “citizens as sensors” (10)—may create opportunities for researchers to more effectively use GIS information. They also may permit location-based context-sensitive ecological momentary assessment (e.g., ask a particular question only when a person is known to be in a park). Creating these databases may be more of a social and administrative challenge than a technical one, as GIS researchers report that both public and proprietary GIS databases are difficult to assemble, access, update, evaluate, and fix, and researchers may be skeptical of open GIS data sources (18).

Battery Life—Battery life of devices will improve to some extent. However, by leveraging devices that subjects may already charge regularly, such as mobile phones, researchers may be able to overcome battery limitations. For instance, suppose a sensor is embedded in a phone that gathers accelerometer and location data. If the phone is kept charged by the subject because that person requires or enjoys the capabilities the phone affords, the battery life of physical activity/location sensing will be adequate as long as it does not disrupt normal phone usage.

Environmental Sensors—Applying sensors to measure a person’s environment is becoming increasingly practical. For instance, radio-frequency identification stickers that cost less than $1 can be placed on objects in a home and used to detect location and type of a person’s everyday activities (21). Such technology could be deployed in settings where physical activity is common (e.g., gyms), or could be placed in the homes of participants to measure interaction with objects, such as exercise equipment, as well as other objects that may influence physical activity or energy balance, such as televisions and computers. Used in combination with motion data, such sensing may further improve activity inference algorithms.

Emerging Trends in Methods

Emerging trends in sensing devices and techniques will create new opportunities in methods for improving compliance and interventions.

Interactive Compliance Aids—The ability for devices, particularly mobile phones, to detect wear time and respond instantly with feedback to study participants could dramatically increase compliance, thereby protecting statistical power by maintaining the majority of recruited participants. However, concerns about measurement reactivity, or the effect of the measurement on the participant's behavior, must be explored.

Remote Compliance Monitoring and Data Collection—The ability of devices to send data to research servers using cellular data networks permits daily remote monitoring of study participants by simply logging onto a secure website. Only participants who are clearly out of compliance need to be contacted, saving staff time. This methodology also allows technology that is broken to be quickly identified and replaced. Once data are transmitted to the research team, they can be removed from the device, possibly extending deployment time. Finally, data can be cleaned incrementally, reducing time from data collection to data analysis.

Long-term Studies with Objective Measures—Mobile phone-based methods will allow study participants to download study software. Data can then be sent to the research server and compliance can be monitored remotely. The researchers running the study do not need to recover the phone, and there is no reason that data collection must be limited to a week, several weeks, or even several months. In some cases, it may be possible to run studies for years with little administrative overhead, where tools automatically process incoming data, and researchers can subsample from within long timeframes of data collection.

Studies with Large Sample Sizes—Methodological innovations, such as remote data collection and compliance monitoring using mobile phones that people already own, may make studies with thousands or tens of thousands of participants affordable. This makes data-driven discovery feasible, where algorithms mine massive datasets for unexpected trends (8). Data-driven discovery may complement the hypothesis-driven style of research most commonly used today.

BEST PRACTICES

Recommended Best Practices for Engineers and Device Developers

We encourage engineers and device developers to use the validation protocols defined in this supplement when introducing a new device, to establish consistency and uniformity with previous devices. Additional steps will maximize the research impact of new devices.

- Engage health researchers in building the technology, starting at the earliest stages of the design process. Ideally, grant makers would fund collaborations that permit iterative development and testing of measurement and intervention technologies to support this goal.
- Create devices that save raw data using international standards (e.g., standard gravity) versus proprietary units (e.g., counts) to facilitate cross-device comparisons. Where necessary to extend limited data storage, create a fully specified path from raw data to intermediate feature that is reproducible by others.

- Explore how instrumentation of the environment, in addition to instrumentation of the body, might be used to gather new types of data on physical activity-related behaviors and their contexts.
- Develop proof-of-concept sensors that show the viability of using consumer technologies to collect high-quality physical activity data, and develop prototype data visualization and analysis tools that demonstrate the potential of data-driven research methods with large datasets.

Several gaps in physical activity measurement sensing and tools would benefit from additional effort from engineers and device developers:

- Sensors that improve device compliance. Two areas to explore are sensors that never need to be removed from the body and sensors that proactively detect non-compliance and automatically encourage proper use.
- Non-obtrusive measurement of sleep states.
- Web-based, incremental screening of data using visualization tools that help identify missing data, extreme values, and data that violate common sense.
- Detection of resistance activities and muscle activation. A breakthrough with a comfortable, practical sensor would provide the physical activity measurement community with a missing tool.
- Heart rate monitoring, where variability due to physiological versus psychological responses can be differentiated.
- Development of open GIS databases and support tools so that physical activity researchers can work with others to improve GIS data sources. Collaborations with major mapping and GIS database companies such as Google and Tele Atlas may accelerate these efforts and permit GIS data contributed by the general public (10) to be used for health research as well.

Recommended Best Practices for Measurement Scientists and Statisticians

Measurement scientists and statisticians can take steps today using existing devices to accelerate the introduction of new technology in the near future.

- Provide specifications for sensor devices, such as what they should measure and in what units, where no component of the specification is proprietary.
- Establish a consensus that devices that output proprietary units should also output raw data.
- Provide a prioritized list of well-specified activities and categories of activities, as well as other physiological states that need to be measured. Set out specific measurement challenges for device developers and include clear validation protocols. These protocols should consist of: (1) bench tests that measure device response across the full range of expected behaviors and physiological states; (2) algorithmic tests using bench test data that compare device output against current and past devices, using archived, raw datasets so that not all devices need to be physically tested together; (3) lab tests that measure device response to small but likely variability in body placement during a set of common postures and ambulatory activities; and (4) field tests that measure device response to important postures, ambulations, and everyday activities.
- Share raw datasets in common formats in online repositories that facilitate reuse and cross-study and cross-device comparisons. Such repositories may create

incentives for algorithm developers to improve and share models and sensors, as they have done in other fields, such as electrocardiogram analysis (9).

- Look to other fields, such as gait recognition, activity of daily living recognition, machine learning, and ubiquitous computing, for alternative methods to process raw signal data. In addition, use sensor fusion to detect not only gross levels of motion but specific behaviors or contexts.
- Develop resources to facilitate finding, archiving, visualizing, and reusing not only the datasets, but the algorithms used to process them. These resources should include tutorials to help investigators apply comparable methods across studies and easy-to-use versions of promising algorithms that run in freely-available tools such as Weka (28) and R (24), so researchers can easily adopt new techniques and compare them. A central list linking to existing databases would facilitate this goal.
- Develop data analysis methods that can use time-series data of activity type, amount, and location, where the data are assumed to be inferred from multi-sensor systems that detect activity states with some quantifiable uncertainty.
- Develop research projects or a central research service that evaluates equivalency between devices using bench, lab, and field tests and creates tools that simplify data collection, verification, annotation, and sharing.
- Begin testing the impact of real-time compliance feedback on physical activity reactivity and determine whether this is a serious concern.
- Seek out engineers and device developers to write reviews of technologies for conferences and journals and collaborate in planning long-term physical activity measurement device development.

Recommended Best Practices for End Users of Measurement Systems

Researchers using existing devices can take steps to maximize the research value and comparability of their current datasets when future devices are in common use and current devices are no longer available.

- Adopt, as soon as possible, devices that do not have proprietary components at any point of the chain of converting from raw data to final output (e.g., counts, energy expenditure), reducing reliance on device-specific, proprietary count units.
- Whenever possible, collect data and save data in raw formats and process afterward into summary features (e.g., counts) using well-described algorithms.
- Whenever possible, pilot a new device simultaneously with standard devices, so comparability can be assessed.
- Publicize the practical lessons learned from studies, including the problems that were encountered, for the benefit of engineers. If such observations will not appear in outcomes papers, publish them on the Internet. The practical challenges and the tricks used to overcome them will help engineers design better devices. Highlight the missing information that would have helped interpret the data, run the study, or lower the study’s cost.
- Report on the total cost of using a technology, including the staff time required for training, compliance monitoring, fixing devices, and other issues. This information will help engineers develop new tools that may reduce overall research costs, as well as the costs of the devices themselves.

Recommended Best Practices for All Groups

The following best practices are recommended for all investigators.

- Encourage multi-disciplinary teams to develop tools for managing and checking data remotely on devices and to run pilot studies on flexible sensor platforms.
- Encourage and organize tutorials and panels at conferences to educate researchers about the long-term value of using technology that fully specifies how all aggregate summary measures (e.g., well-defined versions of counts) are computed. The benefits will be higher-quality and higher-fidelity data obtained at lower costs and with larger sample sizes.
- Supplement Pubmed literature reviews with searches in databases where engineering papers are indexed, such as IEEE, ACM, Springer, Elsevier, and Google Scholar.

FUTURE DIRECTIONS

Below we discuss several trends that could evolve over the next 5 years.

- More devices may emerge that take advantage of motion measurement in three dimensions, reducing device sensitivity to body orientation and/or allowing an estimate of work done by particular parts of the body (e.g., arms vs. legs).
- Devices that log data using onboard memory will be capable of storing summary data for months or raw accelerometer data (60+Hz, 3-axis) for one or more weeks on a single charge. These devices will be about the same size as, or smaller than, existing devices.
- Researchers will have the ability to change the focus of their measures from proprietary counts to summary data computed from raw accelerometer signals, where the summary feature computations are fully and openly described. This should facilitate comparison across different devices. Efforts to define standards for cross-device validation and openness, such as in this supplement, can accelerate these changes.
- Sensors will be sufficiently small and convenient so that it will be possible to have participants comfortably wear more than one sensor at different body locations under clothing. Devices that integrate information from more than one body location may dramatically improve the fidelity of physical activity data that can be collected from participants.
- Systems may improve activity type and amount detection performance using statistical pattern recognition algorithms that not only use motion features from accelerometers, but also information from other types of sensors (e.g., location).

In the longer term, it is possible that a system could:

- Be downloaded from an “app store,” directly onto a standard mobile phone;
- Use entertaining ways to teach participants to use and wear it, while collecting training data;
- Detect overall physical activity level if carried in the pocket or on the hip;
- Detect specific types of physical activity such as postures, ambulation, and even resistance activities if used with one or more additional wireless devices that communicate with the phone;

- Provide entertaining audiovisual feedback to prompt participants when it is not working or being worn properly;
- Provide engaging f b eedback to the participant using the detected physical activity information, such as applications for health monitoring, time management, or even games;
- Transmit data about physical activity and compliance to researchers daily;
- Create long-term, second-by-second activity maps for researchers, overlaid on location where the activity took place; and,
- Provide new opportunities to create interventions that influence in-the-moment decision making with tailored, just-in-time feedback.

CONCLUSION

Few measurement devices in use today will be on the market 10 years from now in an identical form. Internal electronic components, firmware, wireless chips protocols, and housings are all likely to change as old technologies are supplanted by improved or lower-cost options. Longitudinal studies using current technologies will need lab and field tests that show equivalence between "old" and emerging devices and the datasets they generate. Following the recommendations proposed here, such as saving raw data whenever possible, as well as those presented elsewhere in this special issue, may facilitate such "bridging studies." In order to maximize the impact of physical activity measurement research being conducted today, investigators *must* expect and plan for change so as to fully exploit the potential of the new devices on the horizon.

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