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RE-DEFINING THE ROLES OF SENSORS IN OBJECTIVE PHYSICAL ACTIVITY MONITORING

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Abstract

Background—As physical activity researchers are increasingly using objective portable devices, this review describes current state of the technology to assess physical activity, with a focus on specific sensors and sensor properties currently used in monitors and their strengths and weakness. Additional sensors and sensor properties desirable for activity measurement and best practices for users and developers also are discussed.

Best Practices—We grouped current sensors into three broad categories for objectively measuring physical activity: associated body movement, physiology, and context. Desirable sensor properties for measuring physical activity and the importance of these properties in relationship to specific applications are addressed, and the specific roles of transducers and data acquisition systems within the monitoring devices are defined. Technical advancements in sensors, microcomputer processors, memory storage, batteries, wireless communication, and digital filters have made monitors more usable for subjects (smaller, more stable, and longer running time) and for researchers (less costly, higher time resolution and memory storage, shorter download time, and user-defined data features).

Future Directions—Users and developers of physical activity monitors should learn about the basic properties of their sensors, such as range, accuracy, precision, while considering the data acquisition/filtering steps that may be critical to data quality and may influence the desirable measurement outcome(s).

Keywords

transducers; devices; motion sensors; physiological sensors; contextual sensors

INTRODUCTION

The application of objective portable physical activity monitors has a long history extending from foot contact switches and mechanical pedometers with gear-modulated counters to single and multi-sensor accelerometer networks with integrated microprocessors and digital displays. These motion sensors also can be combined with physiological sensors, such as heart rate, temperature, and heat, to estimate the intensity of physical activity prospectively.

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In a previous review, Chen and Bassett (6) described the technologies of accelerometry-based activity monitors up to that time. Within the same timeframe, Mathie et al. (37) also published an excellent review that covered the extensive use of accelerometers in biomechanical measurement applications such as gait measurements, sit-to-stand transfers, posture sways, and falls. Since then, some changes have occurred in the technology used in activity monitoring that have not been covered by several recent reviews (13, 23, 39, 42, 57). Therefore, our goal is to identify the desirable properties for measuring physical activity found in both widely-used and newly-developed sensors, and to understand how their properties may differ according to the application.

A sensor generally refers to a device that converts a physical measure into a signal that is read by an observer or by an instrument. We live in a world filled with sensors for different functions, ranging from simple mercury thermometers for measuring air temperatures, to sophisticated biomedical sensors for detecting brain activities. Their size can range from nanosensors implanted in the body, to magnetic resonance imaging scanners that occupy a large room. Despite these enormous differences, all sensors have similar fundamental properties defined by sensitivity, range, accuracy, precision, and the need to be calibrated against known reference standards. Sensitivity indicates how much the sensor's output changes when a measured quantity changes. Range describes the minimum to maximum quantity change that the sensor is capable of measuring. Accuracy refers to the degree of closeness of a measured quantity to its actual or true value. Finally, precision is the degree to which multiple, repeated measurements of one quantity differ. These basic properties are important when we design, calibrate, use, and model output data for the purpose of objective physical activity monitoring.

Technically speaking, sensors are made of two major components: (1) sensing elements, or transducers, which convert one type of energy (e.g., motion) or physical attribute (posture) that is hard to measure to another (voltages) for the purpose of easier measurement; and (2) data acquisition devices for digitally sampling the converted energy form, transforming it into a signal, and processing it to retain the desirable parameters and quantities while discarding or suppressing the noise and artifacts. As users, we usually see the output in signals that have been processed, without acknowledging that the properties of both components can ultimately influence the quality of our signals of interest.

CURRENT TECHNOLOGY

Currently, three general categories of sensors can be used for measuring physical activity in humans: movement sensors, physiological sensors, and contextual sensors. Depending on the desired outcome measures, a sensor or a combination of sensors (arrays or networks) can be used for multiple purposes.

Movement Sensors

Many movement sensors can be used to measure human physical activities, including electromechanical switches (for heel strike detections), mercury switches, pedometers, inclinometers, gyroscopes and goniometers (for angles or postures), and accelerometers. Even global positioning systems (GPS) can now be added to the list. Among these devices, accelerometers are currently the most widely used sensors in human physical activity monitoring in clinical and free-living settings.

Transducers—Only a few years ago, most sensing elements of accelerometers were piezoelectric transducers configured in cantilever beams with seismic masses (6), which were typically installed manually by experienced technicians and calibrated during manufacturing processes. This was time-intensive and most likely resulted in increased costs and inter-unit variability.

Technological progress since then has allowed more transducers to be developed and manufactured on a microscopic scale. In most cases, the microscopic sensor is referred to as a micro electro mechanical system. These sensors have the capability of reaching a significantly higher sensitivity compared with macroscopic approaches while reducing power consumption for expanded measurement length. Multiple micro electro mechanical system transducers for measuring movements in different directions can be packaged into a signal sensor enclosure using precision machine assembly, compared to the process of manually installing individual sensors (e.g., piezoelectric beams) in the portable physical activity monitors with different mounting angles, which are prone to variabilities. In addition, the use of micro electro mechanical system sensors can reduce overall size, increase durability, and reduce manufacturing costs of the portable monitors. Combined with improved microprocessors, expanded on-board memory, extended battery life, and wireless communication, technology has allowed us to ascertain improved objective measurements of physical activity. In most cases, these improvements have permitted physical activity measurement for longer periods and with higher time resolutions than before, and in some cases with improved accuracy.

Acceleration transducers also have switched from the piezoelectric cantilever beam to piezoelectric or piezoresistive compressive integrated chips or differential capacitance accelerometers. Compared to a piezoelectric crystal, a piezoresistive accelerometer uses a substrate that changes resistance when it is subjected to mechanical deformation. Most of these transducers are now micromachined within or on the surfaces of a polysilicon structure. A differential or variable capacitance sensor is typically constructed with plates attached to the moving mass and fixed plates, and the capacitance between these plates is dependent on the distances between the plates as an acceleration is applied to the moving mass (Figure 1). The piezoresistive and differential capacitance accelerometer are sensitive to both gravitational acceleration and motion-induced accelerations.

The micro electro mechanical system is becoming the new industry standard in low range (<16 g) micro accelerometry transducers at the present time. For instance, in the two most recent generations of ActiGraph (Pensacola, FL) accelerometers (GT1M and GT3X), the piezoelectric cantilever sensor found in the 7164 and 71256 monitors has been replaced by a monolithic differential capacitance sensor with dual axial and triaxial measurement capabilities, respectively. In addition, on-board memory has been expanded to allow data collection at higher time-resolutions (raw data mode at 30Hz, or time-integrated signals from 1-second to 15-minute epochs). Moreover, the GT1M monitors have incorporated “self-calibration” during initialization, resulting in a significant reduction in intra-device variability (45). Despite these advances, the ActiGraph still has limitations. The comparability between generations of sensors has not been entirely preserved with the transition of these sensors (45, 47). Similarly, the Actical monitor (Mini Mitter /Respironics/ Philips, Bend, OR) changed their omni-directional cantilever beam to a compressive piezoelectric transducer in an integrated chip (IC) in 2007. In contrast, to our knowledge the RT3 (Research Tracker, StayHealthy, Inc., Monrovia, CA) has remained unchanged since our last review. For specific properties of each transducer, readers should contact the manufacturer. Sensor comparability is an important consideration for cross-project comparisons or for longitudinal analyses in existing studies, as some physical activity monitors become discontinued and replaced by new monitors (or new transducers or other hardware modifications) of which investigators may not be entirely aware. In this supplement, Welk et al. have discussed how to cross-validate between different types of monitors.

Data Acquisition Systems—Because most users of motion sensors rarely store and analyze raw signals collected directly from the transducers, the process of filtering the signals is essential to obtain desirable measurement parameters. Although the transducers are sending readable signals to the monitor, it is the role of the data acquisition systems to recognize, sample, condition, and process them. To accomplish such complex tasks in current physical activity monitors, manufacturers use the combination of firmware and software. Firmware usually controls basic device functions, such as configuration of data, logic programming, and communications within and between hardware components using machine-level commands and programs that are stored onboard the processors. Software, on the other hand, handles computer operations that interface with users, can be used to configure various firmware options when the device is connected to a personal computer, and manages data transfer (both uploads and downloads).

Almost all current accelerometry-based activity monitors report their outcomes in counts per unit time or epoch. However, as reported previously (6), due to different transducers, amplifiers, sampling frequencies, and signal filters, different types of monitors give different count values even when measuring the same input accelerations. Some current monitors have begun to offer additional outcome parameters, such as step counts, estimated body positions, and monitor wear status, which are all extracted from either raw signals or just after band pass filtering. Future studies need to validate the accuracy and precision of these outcome measures.

Most of the current accelerometry-based activity monitors employ band pass filters to extract certain frequency ranges of the collected acceleration signals while “filtering out” signals in the frequency domains that are not likely to be “physiological.” Some manufacturers publish their band pass filter ranges (a typical band width for a hip or waist worn accelerometer is 0.2–3.0 Hz) but rarely release their performance data. We have only recently learned more about these filters. Using a treadmill test and field tests in healthy adults, Brage et al. (5) found that the CSA (the predecessor of the ActiGraph) output was fairly linear (R^2=0.92, p<0.001) with increased speed during walking (3 to 6 km/h) and running (up to 9 km/h) in adults. However, the signals exhibited a plateau from 9 to 20 km/h. Rowlands et al. (47) found similar behavior in ActiGraphs worn by adults and children (4). Beyond the potential that the acceleration at the center of mass may be reduced in running versus walking, the overly aggressive frequency-dependent filtering also was suggested as the cause for the plateau effect. Rothney el al. (45) used a modified bench-top orbital shaker and showed a robust non-linear sensor response to increasing frequency and acceleration amplitude in all three generations of CSA/MTI/ActiGraph monitors. This confirms the limitation of such filtering techniques, which can lead to erroneous measurements of human movements.

In 2008, ActiGraph released a new software option for GT1M monitors that allowed its users to collect data in raw (30 Hz) and unfiltered mode. The new GT3X monitors also have this option. To investigate how the filter influences measurements, we placed three GT3X monitors on the same orbital shaker used in our previous study (45). The monitors were programmed with raw unfiltered, raw filtered, and 60-sec epoch (filtered) modes, respectively. We increased the shaker speed from 25 to 225 rpm, and each bout lasted about 6 minutes with at least 2 minutes pause between each bout (Figure 2). We again observed plateau effects around 125–150 rpm ranges in both the 60-sec epoch and raw filtered modes, while the absolute dynamic signals in the raw unfiltered mode was increasing with the rpm. These observations confirmed the field findings by others (4, 47) and further demonstrated that this plateau effect was primarily due to deficient filtering as compared to normal running mechanics. Moreover, acceleration signals at lower shaker frequencies were also suppressed by the filter, seen by the signals in the raw pre-filtered mode, as compared to no observed signals in the raw post-filtered and 60 sec integrated signals, which was consistent with our previous findings (45).

To further confirm our bench findings, we mounted two new GT3X monitors on each hip of one healthy study volunteer, while he performed different activities. Figure 3 shows a reduced acceleration signal (vertical axis) during sprinting (19.2 km/h) as compared to running (12 km/h), possibly due to the filtering, which was similar to what we found on the shaker. Together, these data confirm that even the most commonly-used accelerometers must be empirically tested. And since digital signal processing filters are now commonly applied to micro electro mechanical system sensors, their specific properties and functions should be more rigorously studied in the future. We also should call on device manufacturers to be more transparent in releasing the filtering information to aid in this effort.

Summary of Current Movement Sensors—Collectively, accelerometers are well-suited for measuring intensity of movements, thus are predominately used for assessing outcomes, such as overall physical activity levels and estimated energy expenditure. The small packaging, relative stability over time, minimum user interface, good dynamic ranges, long monitoring times, and independence of motion parameters from other physiological changes are all strengths of movement sensors. Currently, micro electro mechanical system accelerometers are the principal class of motion-detecting transducers due to their small size, affordability, low power consumption, multiple axes, variable ranges, linearity, good sensitivity, and in some models, the capacity to measure gravitational loads and orientations.

However, except for a few new monitors (e.g., activPAL [PAL Technologies Ltd.,Glasgow, Scotland]), most current accelerometry-based activity monitors lack sensitivity for further partitioning sedentary behaviors, such as sitting, standing and even slow walking, perhaps due to their inherent transducer limitations (piezoelectric) and overly aggressive filtering. The overly aggressive filtering may affect measurement accuracy on both ends of the activity spectrum (low and high intensity). With improved data accessibility, such as multisensor arrays/networks and the ability to increase data time resolutions, and more sophisticated modeling approaches, research has made steady improvements in these areas (12, 43, 46).

Best Practices and Recommendations—Because we use accelerometers to measure movement, we need to ask which properties of human movement need to be considered. Two important parameters related to the acceleration of motion are frequency and amplitude, which depend on the segment(s) of the body where the sensors are attached. Welk (56) indicated that the acceleration of the body is typically less than 10 Hz, with the majority of daily physical activity-associated movements at the center of mass in the range of 0.3–3.5 Hz (37). However, we know that foot acceleration can reach up to 60 Hz during the heel strike of walking and running and significant shifts of the power spectrum of the signal toward 15–18 Hz. With regard to amplitude ranges, Mathie et al. (37) suggested from ± 0.2 g at the head, −0.3 to 0.8 g at the upper body (vertical direction) during walking, and up to 8.1 g at the ankle during walking down the stairs. Given these biomechanical range factors, our current accelerometry-based monitors may only be sufficient to cover crude daily activities. Therefore, if the desired clinical question is how heel-strike accelerations affect bone turnover, we need to identify a feasible location (e.g., ankle or knee) and transducer measurement range to acquire that information.

In addition to transducer ranges, data acquisition system performance also is critical, particularly regarding the sampling rate and digital filters used. The minimum sampling rate is guided by the Nyquist principle, which states that sampling rate should be greater than or equal to twice the highest frequency contained within the signal. Following the general guidelines listed above, a 30 Hz sampling rate or higher would be sufficient for ascertaining general movements in the trunk, but may not be suitable for specific applications such as detecting gait patterns and peak accelerations during running. Digital signal processing filters are routinely used in the data acquisition system due to their ease of implementation. As we have shown here, the band pass filter plays an important role in determining the quality of the output from these monitors. Deficiency in filter selection can lead to loss in signal detections (e.g., lack of sensitivity in low-intensity movements and plateau in high-intensity movements). Future studies and developments in this area are warranted. Furthermore, many accelerometry-based activity monitors today still output activity counts. Because these are arbitrary units that are determined by the data acquisition system and lack physical meaning and comparability among different monitors, future models should provide standard units, such as gravitational constant (g, m/s^2) or time-integrated units (e.g., m/s).

Physiologic Sensors

Physiologic sensors include heart rate, gas exchange (O_2 and CO_2 in breath and in blood), blood pressure, temperature (skin and core body), heat flux, sweating (galvanic skin response), blood chemistry (continuous glucose), electromyogram (electrical activity of muscle), and breathing frequency and volume. Some of these sensors have been used independently or in various combinations with one another and with accelerometers for measuring physical activity (e.g., Actiheart, Cambridge, UK; SenseWear Armband, Bodymedia Inc., Pittsburgh, PA) (3, 11, 17). The properties of these sensors vary widely depending on the applications or manufacturers and development laboratories that produce them. The sensor technologies and the models used for predicting outcomes, such as activity type or intensity, are often proprietary, making detailed evaluation and improvement difficult for researchers. However, with careful calibration and appropriate statistical modeling, physiological sensors can increase the sensitivity and the accuracy of the measurement of energy expenditure and/or activity type. This approach may be particularly important when monitoring populations not well suited for a single, accelerometer-based sensor such as cyclists, swimmers, and non-ambulatory individuals. Moreover, these sensors measure the physiological responses from activities, which may offer more clinically relevant parameters with which to examine the relationships between physical activity and health.

Heart Rate Monitors—To date, heart rate monitoring remains the most common single-sensor physiologic monitor. Throughout the range of moderate through vigorous physical activity, heart rate increases linearly and proportionately with the intensity of movement and the volume of oxygen consumed by the contracting skeletal muscle, making it a sensitive indicator of activity intensity and useful in estimating physical activity energy expenditure. Additionally, heart rate is a well understood and defined phenomenon and there is greater agreement in standards for measuring, filtering, and storing heart rate data than for accelerometer data.

Like all physical activity monitors, heart rate monitors consist of a transducer and the data acquisition system. With few exceptions, heart rate monitors use a series of two or more electrodes transducers worn at the chest. Portable heart rate data acquisition systems are typically worn at the waist or wrist and acquire signal from the sensors wirelessly, although a few devices (e.g., Actiheart) house the data acquisition system and sensing elements in one unit worn on the chest. The data acquisition system digitizes, time integrates, and stores heart rate signal by calculating a moving heart rate average for short preprogrammed epochs (usually 5 to 15 seconds) determined by the investigator. Some newer monitors (e.g., Polar

RS800 series, Cambridge NeuroTech Actiheart) are capable of storing the timing of each heart beat (Interbeat Interval or IBI series) for several hours, which can be used to calculate heart rate variability.

Practical considerations involved in heart rate monitoring include susceptibility to noise, generally from 60-Hz electrical interference through common household devices such as televisions and computers, motion artifact, and loss of contact (27). These issues can be minimized by positioning the transducer and data acquisition system close together, and by using electrolyte gel to increasing sensor-to-skin surface area and ensures firm sensor-to-skin contact. However, most individuals find it uncomfortable to wear a sensor all day that is secured tightly to the chest. In some individuals, contact dermatitis and skin chafing can occur. Resolving these issues is critical to advancing the use of this technology, particularly when the outcome of interest (habitual physical activity) requires multiple days of monitoring. Recent developments, such as non-woven fabric sensors with specialized electrophysical properties may be used as functional clothing, eliminating the use of stick-on electrodes or chest straps (29).

Despite these practical limitations, laboratory and field research examining the accuracy and precision of currently available heart rate monitors indicates good to excellent agreement between the most commonly used monitors and electrocardiogram recordings (2, 22, 30, 55). In some situations, the use of heart rate as a measure of physical activity, as opposed to motion-based physical activity sensors, may be exploited to better understand various activity and health outcome relationships. For example, heart rate monitoring has recently been used to examine the contribution of horseback riding to daily activity levels and functional fitness in wheel chair and ambulatory children with cerebral palsy (16). Furthermore, as heart rate is a parameter in the time domain, the absolute amplitude of the electrocardiogram signal is not critical, as long as it has a good signal-to-noise ratio to allow heart rate detection. Therefore, in contrast to accelerometer-based activity monitoring studies, heart rate monitoring studies have greater comparability even when different monitors and data modeling strategies are used.

One major limitation of using heart rate for physical activity monitoring is the relative nature of this index. Both resting heart rate and basal heart rate variability levels depend on individual fitness level, autonomic status, and presence of cardio-active medications. Heart rate increases are relative to the stress placed on the cardiorespiratory system and individuals participating in the same activity have different heart rates based on their cardiovascular fitness. Other considerations include changes in heart rate that occur independent of physical activity, such as emotional or environmental stresses.

As the technology advances, greater data resolution and storage should allow for mathematical modeling of heart rate data similar to advances currently being tested with accelerometer-based activity monitors (50). Predicting energy expenditure using heart rate data could theoretically reduce measurement error associated with the current linear regression approaches and, perhaps, eliminate the need for separate calibrations for each individual monitored. Greater resolution and increased memory also will allow for more precise after-the-fact data cleaning, fewer data points lost, and reduced error.

Temperature and Heat-flux Sensors—Several attempts have been made to augment the picture of human physical activity using sensors that detect either absolute temperature, such as Vital Sense (by Respironics/Philips, Bend OR), or one or more components of heat flux, such as SenseWear Armband and LifeChek (by LifeChek Medical Devices, Pittsburg PA). In the measurement of absolute temperature, sensors can be placed anywhere on the surface body using dermal patches to detect changes in skin temperature or given as a pill to monitor the core body temperature. These devices typically communicate with a data acquisition system through radio-frequency (RF) telemetry and are capable of logging temperature once each minute. Heat flux sensors are typically worn as armbands, and both sensor and data acquisition system are housed in a single connected unit. The SenseWear Armband was the pioneer in using convective heat flux, in combination with several other physiologic signals (skin temperature, galvanic skin response, and accelerometry) to monitor physical activity and energy expenditure (26). Recently, however, LifeChek has introduced an armband capable of sensing all four components of heat flux, (conductive, evaporative, radiative, and convective) and its output appears to track well with energy expenditure measured through indirect calorimetry (38). However, studies are preliminary at this point, and the contributions of these various flux components in monitoring physical activity and estimating the energy expended have yet to be established.

From a usability standpoint, many of these sensors have similar limitations to the heart rate monitoring devices: the dermal patches used to monitor skin temperature can cause contact irritation and must be covered or replaced after showering for longer studies. Core temperature capsules are invasive by nature (albeit mildly), and significant distance (e.g., more than 3 feet) between the sensor and data acquisition system can cause substantial data dropout. Armbands used for heat flux sensors also cause subject discomfort, which may lead to compliance issues.

Several issues with temperature and heat flux sensing devices are still unresolved from a measurement standpoint. One such issue is the time lag needed to dissipate heat from the body upon completing moderate or vigorous exercise. While these temperature and heat flux devices may be useful for estimating energy expenditure, caution should be taken when assessing physical activity. These sensors also measure local changes in heat flux and temperature and extrapolate to the level of the whole body. In many cases, the effect of additional layers of clothing and changes in environmental temperature are not taken into account. The algorithms for heat flux sensing monitors to estimate energy expenditure are mostly proprietary. Consequently, the contributions of each component of heat flux and other physiologic measurements are unknown, making calibration and routine checks of data quality from each component impossible.

Other Physiologic Sensors—Some additional physiologic sensors may be useful for measuring specific components of physical activity that could not be achieved using movement sensors, such as using an electromyogram to assess skeletal muscle function (25) and implantable sensors to detect blood glucose levels. Limitations of these sensors include the intrusiveness and invasiveness of some (e.g., masks for breath sensors and implanted blood glucose sensors), accuracy and precision (surface electromyogram), and controls for intra-individual variability (heart rate). We have seen limited success in the past several years in devices such as the SenseWear Armband, that combined several of these sensors in a small and wearable device for measuring energy expenditure and estimating the time spent during basic activity types such as sitting and lying down. Actiheart is another device that combines the simultaneous data streams from an accelerometer and heart rate to estimate energy expenditure in children and adults. Such approaches have been found helpful in predicting energy expenditure compared to single-site accelerometer-based activity monitors (3, 7, 11, 17). However, given the increase in cost and decrease in compliance, the improved precision may not always be justified (7).

Contextual Sensors

Traditional sensors are primarily engineered to measure quantity and patterns of physical activity, focusing mainly on intensity, duration, frequency, and type. Contextual sensors, on the other hand, are concerned with assessing the context or environment in which the physical activity is being performed. Compared to motion and physiological sensors, contextual sensors are relatively new and have great potential to help describe the relationship between physical activity and various environmental features (48), such as urban infrastructure and transportation (15, 18), workplace design, and the home environment (9, 14, 36) by capturing the location and the surrounding environment.

The requirements for the sensors may differ according to the range/area they can cover. Thus, they can generally be classified into two broad categories, global and local. A "global" sensor, such as global positioning system (GPS), and its network can cover a very large region or area. This device, so commonly used in our daily lives, has found a new application as a physical activity assessment tool (32, 44, 49, 54). Based on the unique information it provides, the new concept of "PA space" has been proposed. Physical activity space is defined as "the area or space where an individual spends time and engages in physical activities" (60). In contrast, "local" contextual physical activity sensors describe the context of a person's physical activity in a limited area. Most research using "local" contextual physical activity assessment comes from the research of the "Smart Home" or "Assistive Living" (14, 36). As this is an emerging field of research, the nomenclatures of "global" and "local" are relatively arbitrary at this time.

Global Contextual Sensors—GPS sensors are capable of triangulating their location, including elevation, by receiving radio signals broadcast from satellites orbiting earth. This process requires a clear line of sight to a four or more satellites (53). The DAS is typically housed in the same unit as the sensor and is capable of logging latitude and longitude coordinates and distance traveled. The GPS location information can then be mapped to software-based Geographic Information System (GIS) data to identify structures of interest on the route (e.g., transportation, green space, restaurants), helping to address questions relating physical activity and the built environment (1, 19), travel mode selection (10, 34) or leisure versus occupational physical activity (40).

A major limitation of GPS units is that they are capable only of tracking location and measuring outdoor physical activity because of their need for a clear line of sight to the satellites. The signal is interrupted when the wearer moves indoors, travels in a tunnel, or even when the line of sight is obstructed by tall buildings or heavy foliage (51). Several other practical issues with GPS-based monitors include difficulty with initial localization (typically more than 1 minute from a cold-start), limited accuracy in sensing stationary device location (error greater than 1 meter), and limited accuracy in GPS-measured distance (around 5%). The difficulties in using these devices to measure physical activity are explored in much greater detail in the recent review by Duncan et al. (18).

Local Contextual Sensors—Local contextual sensors can be used to answer questions about physical activity within structures, such as work-based activity patterns or movement patterns within the home. Several examples of local contextual sensors are presented below:

Radio-frequency identification: This sensor network consists of pen-sized radio-frequency identification tags, which are placed on a person and transmit radio frequency signals that are picked up by radio-frequency receiver antennae. An application then identifies and logs the location of each radio-frequency identification tag based on its location relative to the antennae. Radio-frequency identification has been used widely in military, business, and healthcare for tracking goods, managing chain supply, and tracking patients. It can now create sophisticated levels of control and visibility in a wide range of applications (59), such as in tracking golf balls (31), monitoring soccer games (8), and time recording for marathon racing. A number of radio-frequency identification applications have been reported in the smart-home research for tracking activities (24, 41). The drawback of this technology is the limited range between the tags and the receiver (approximately 30 m), which require that a number of antennae be placed in static locations to properly track the location of the tags in a large building or urban neighborhood (21). Other related issues include accuracy, privacy, and security (58).

Passive/Presence Infrared sensor: A passive/presence infrared sensor measures infrared light radiating from objects in its field of view and has been widely used in controlling devices such as lights, motion detectors, and burglar alarms. The sensor is often manufactured as part of an integrated circuit and may consist of one, two, or four “pixels” of equal areas of the pyroelectric material. Pairs of the sensor pixels may be wired as opposite inputs to a differential amplifier. A person entering a monitored area is detected when the infrared energy emitted from his/her body is captured by the sensor. Passive/presence infrared has been often used in tracking older adults’ physical activity in daily living such as standing for cooking (33). However, the sensitivity and accuracy of this type of sensor for tracking human physical activity requires further study.

Pressure sensor: A pressure sensor measures force per unit area and has been used for control and monitoring in thousands of everyday applications. Lim et al. (35) installed a series of sensors to pieces of furniture and flooring in a home and demonstrated the early feasibilities of using pressure sensors to record and recognize most activities of daily living.

Other sensors: Many other sensors have been employed in tracking and monitoring people’s activities in smart-housing related research. These include detectors to monitor the opening and closing of refrigerator and cupboard doors, weather stations for hygrometry and temperature, and a kinematic sensor for posture changes. Fleury et al. (20) also used a set of microphones for sound and speech recognition. Similarly, Suzuki et al. (52) developed a network of sensors to monitor older adults’ activities of daily living and instrumental activities of daily living. These sensors included an infrared sensor, a door and window opening sensor, a photoelectric motion sensor, a flame detector, wattmeter, and a carbon dioxide sensor.

Summary of Contextual Sensors—Compared to traditional motion and physiologic sensors, contextual sensors provide assessments of physical activity from a new perspective. However, they also bring their own unique challenges. For example, the sensitivity and accuracy of current GPS sensors may be limited. Moreover, to obtain a complete and accurate assessment of context, a network of multiple numbers and/or types of sensors may be employed. As a result, the cost of such an investigation could be high. Investigators are using various approaches to meet these challenges, such as using accelerometers in combination with GPS to better understand the intensity, timing, and frequency of physical activity in different settings or locations (15, 28). Smart house projects have successfully combined hundreds of sensors (24). These assessments of physical activity contexts provide rich information about individual behavior and the interaction of behavior with the environment. Future research should involve interdisciplinary expertise to fully appreciate what contextual measures are most valuable in understanding behavior. With continued improvements in sensors and wireless communication, it is expected the technological challenges will be overcome in the near future, making contextual sensor-based applications more feasible and effective.

BEST PRACTICES

With recent advancements in sensor technologies, portable devices are becoming increasingly smaller, capable of longer data collection (due to both storage and battery lives), multidimensional, and in some cases, more sensitive. These advancements make them more suitable for free-living daily physical activity monitoring compared to their predecessors only a few years ago. With a fairly large number of devices available on the market, and more being developed, matching the physical activity monitor to the needs of the user is critical.

Investigators using physical activity monitors fall into four general categories: (1) those using data already collected from current or past physical activity monitors; (2) those just beginning data collection and using current monitors; (3) those in the planning stages of a large population study; and (4) those developing new monitors or modifying current monitors.

Recommendations for each of these categories may be different for specific areas, but the basic commonality of the sensor properties, such as sensitivity, range, accuracy, precision, and calibration are critical for all users to acknowledge. For example, all users should consider systematic calibrations of their physical activity monitors (for the end-users with data already collected, if the devices are still available) to establish the range, sensitivity, accuracy, and precision. If multiple types or models of the devices were used for the data collection, the comparability should be tested, and if multiple units of devices (even the same model/type/firmware/software) were used, inter-unit variability should be tested. In data processing and modeling, attention should be paid to digital filters applied to the raw signals and other algorithms that may alter the linearity, resolution, and other properties of the desirable data output.

For users with previously collected data and ongoing data collection, the ranges of sensors of the physical activity monitors, especially motion sensors and some physiological sensors (e.g., heat flux, sweating), may not be sufficient to allow accurate assessments of their desirable outcomes such as different body postures, inactivity, vigorous body movements, and extreme ambient environments. It is important for users who are planning or continuing large population studies, to consider costs (both initial and operational costs), reliability and longevity of the devices, ease of use (both subjects and testers), and comparability (both across projects and across time) of physical activity monitors. To the last point, while the rapid advancements in sensor and micro-computer technology have brought us more sophisticated physical activity monitors in recent years, many others that were used by researchers in large-scale longitudinal studies have been discontinued (e.g., Caltrac [Muscle Dynamics, Torrence CA], Tritrac-R3D [RT3 Triaxial Research Tracker, StayHealthy, Inc., Monrovia, CA], MTI 7164 and 71256, and Actiheart). While we should require the manufacturers to supply comparability data between predecessors and successors, independent calibration between devices always should be performed. Investigators also should consider the possible costs of switching physical activity monitors as not all data will be comparable. Furthermore, the potential gains from some technologies should be balanced with potential losses due to increasing costs of the technologies and/or increasing staff time in data collection and processing, participation compliance, and complexity of the modeling.

Developers of physical activity monitors and their applications (modelers), should be careful while considering the technical specifications of transducers, including size, range, accuracy, resolution, stability, linearity, durability, power consumption, and compatibility. They also should apply robust and appropriate data acquisition systems that contain sufficient resolutions, optimal bandwidth filters, and large enough data storage. Lastly, but perhaps most critically, developers also should understand desirable outcome parameters of interest (e.g., energy expenditure or sitting time, the “what” or “where”) for the users. At the current time, sensor or device technology has opened the door to tremendous opportunities for researchers and developers in the field of activity monitoring. Raw material costs for high-quality sensors, memories, and microprocessors are no longer prohibitive. For example, thanks to the popularity of smart mobile phones and computer/video game controllers that are equipped with accelerometers and other motion and/or temperature sensors, the large-quantity manufacturing of transducers means that prices will decline. Manufacturers often work closely with developers and users of activity monitors to ask critical questions, such as what applications, which parameters, how to go longer with higher resolutions, when to add more sensors, and so on. These collaborations and conversations must continue and should expand. More and more researchers and some consumers are interested in objective activity monitoring. With different demands from different applications, the two most important needs for the developer to have in mind are flexibility (versatility) and usability.

Single-sensor devices currently on the market still have unexplored potential. For example, the importance of inactive lifestyle is being investigated as a potential cause for negative health outcomes. However, most of our current monitors only have the capability of lumping all of the time periods where movements are less than a low threshold to one large component, and further quantification of degrees of low-intensities or qualification of types of movements are not feasible. One reason for this deficiency is largely due to lack of posture detection from the piezoelectric sensors. The new capacitance-based accelerometer micro electro mechanical system sensors are sensitive to positional changes and result in baseline change in signals, which could be harvested for postural detection. Multisensor monitors have more signals to differentiate and integrate for the goal of accurate detections of physical activity characteristics. Investigators should balance the temptation to collect data from more sensors with careful considerations of robustness of the outcome predictions in the cases of missing data from one or more sensors and the complexity of data modeling.

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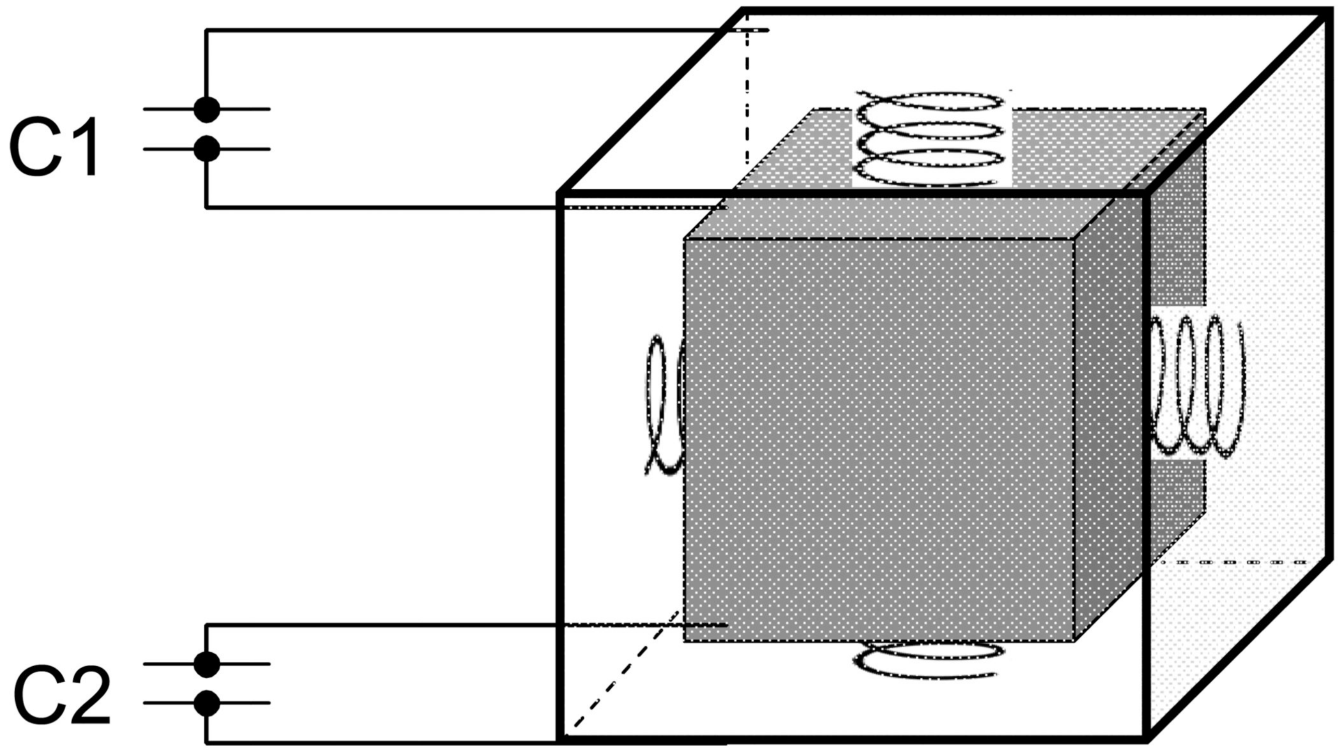

Figure 1.

Schematic drawings of a differential capacitance accelerometer where the capacitances C1 and C2 change as the center mass moves with acceleration along the vertical direction as shown.

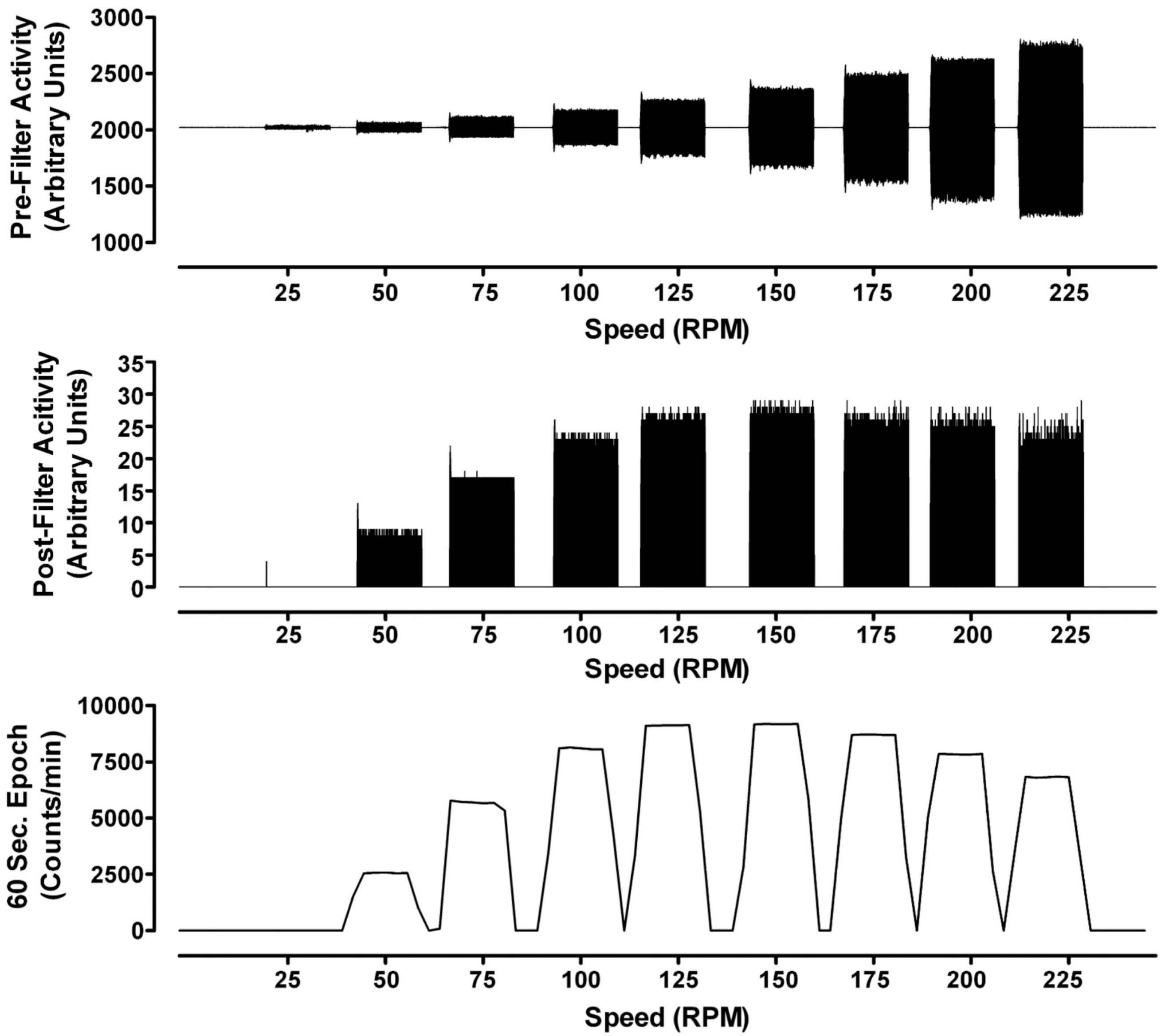

Figure 2.

Sensor output from three Actigraph GT3X monitors varies with different input frequency on a bench-top shaker (radius of oscillation = 46.6 mm). All three monitors were using the firmware 1.3, but were programmed in raw pre-filtered (30 Hz), raw post-filtered (30 Hz), and 60-sec epoch modes, respectively.

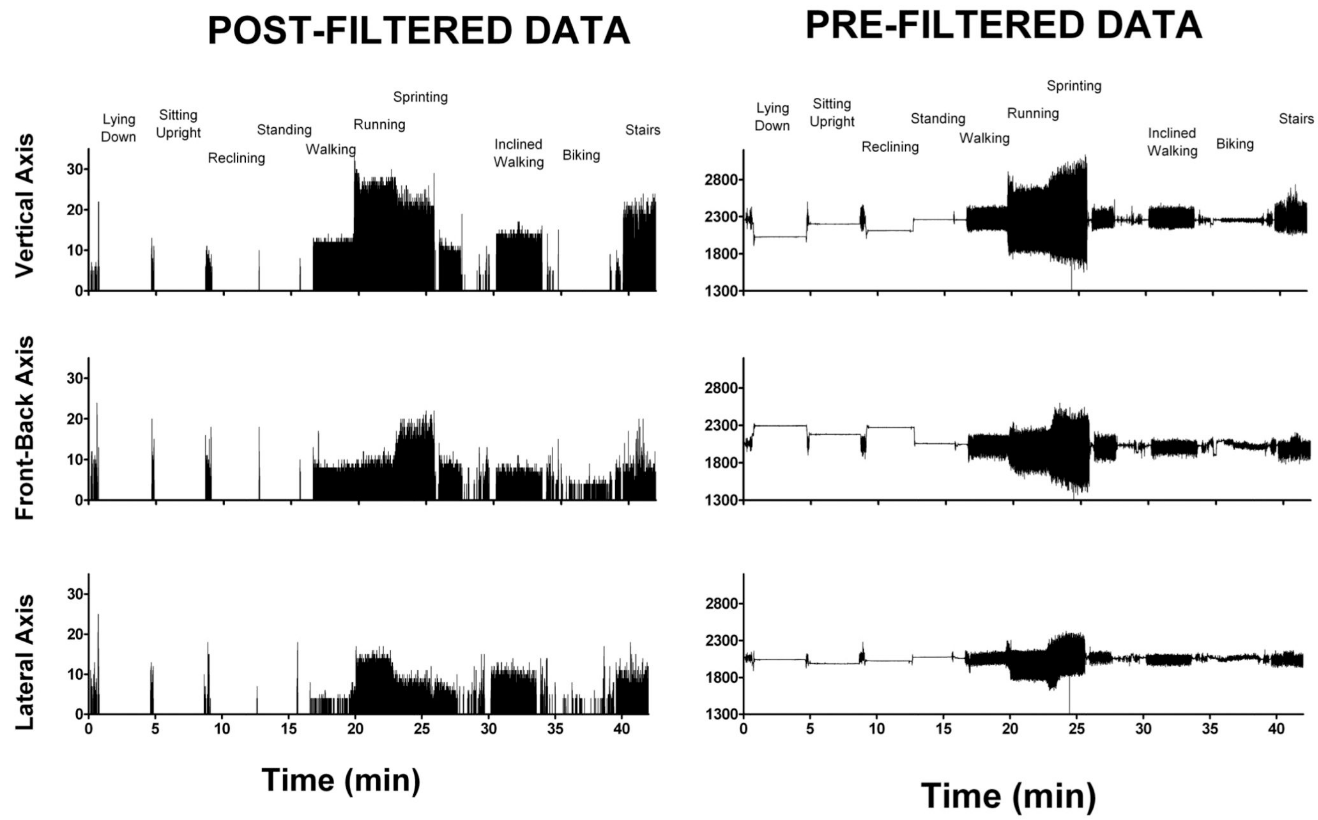

Figure 3.
Two Actigraph GT3X monitors programmed in raw unfiltered (right) and raw filtered (left) modes and were placed laterally on a healthy study volunteer during different activities.