The Technology of Accelerometry-Based Activity Monitors: Current and Future

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ABSTRACT

CHEN, K. Y., and D. R. BASSETT, JR. The Technology of Accelerometry-Based Activity Monitors: Current and Future. *Med. Sci. Sports Exerc.*, Vol. 37, No. 11(Suppl), pp. S490–S500, 2005. **Purpose:** This paper reviews accelerometry-based activity monitors, including single-site first-generation devices, emerging technologies, and analytical approaches to predict energy expenditure, with suggestions for further research and development. **Methods:** The physics and measurement principles of the accelerometer are described, including the sensor properties, data collections, filtering, and integration analyses. The paper also compares these properties in several commonly used single-site accelerometers. The emerging accelerometry technologies introduced include the multisensor arrays and the combination of accelerometers with physiological sensors. The outputs of accelerometers are compared with criterion measures of energy expenditure (indirect calorimeters and double-labeled water) to develop mathematical models (linear, nonlinear, and variability approaches). **Results:** The technologies of the sensor and data processing directly influence the results of the outcome measurement (activity counts and energy expenditure predictions). Multisite assessment and combining accelerometers with physiological measures may offer additional advantages. Nonlinear approaches to predict energy expenditure using accelerometer outputs from multiple sites and orientation can enhance accuracy. **Conclusions:** The development of portable accelerometers has made objective assessments of physical activity possible. Future technological improvements will include examining raw acceleration signals and developing advanced models for accurate energy expenditure predictions. **Key Words:** HARDWARE, ANALYSIS, MODELING, ENERGY EXPENDITURE, PIEZOELECTRIC SENSOR

Physical activity (PA) has been studied for the purposes of understanding the basic characteristics of human movement (e.g., gait analyses) and the relationship of PA to chronic diseases such as cardiovascular disease and cancer. Healthy People 2010 has even recognized PA as a leading health indicator (49). The accurate and detailed measurement of PA is therefore a crucial prerequisite to exploring its association with health and disease.

Numerous methods have been used to measure PA in the short and long terms. They vary greatly in their applicability in epidemiological research, intervention studies, clinical practice, and personal assessment. These methods fall into four general classes: subjective reports and observations, indirect calorimetry, double-labeled water (DLW), and portable monitors. This paper a) reviews the methodologies of the portable PA monitors, particularly the accelerometry-based PA monitors; b) compares the technical and practical aspects of several commonly used accelerometers; c) explores the emerging technologies in the monitor designs; and d) discusses the analytical modeling of monitor outputs in predicting energy expenditure (EE) of PA.

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METHODOLOGIES

Accelerometers are devices that measure body movements in terms of acceleration, which can then be used to estimate the intensity of PA over time. Most accelerometers in current use are piezoelectric sensors that detect acceleration(s) in one to three orthogonal planes (anteroposterior, mediolateral, and vertical). Processed data can be recorded by internal memory and then downloaded through computer ports.

To better understand the accelerometry-based PA monitors, we should understand the basic concepts of the target, namely, the motion or movement associated with PA, the technology of the sensors, and the processes involved from data collection to analyses of outputs.

Basic physics: speed versus acceleration. Speed is the change in position with respect to time. Acceleration is the change in speed with respect to time. Acceleration is usually measured in gravitational acceleration units (g; 1 g = 9.8 m·s^{-2}). When acceleration is zero, the body of interest is no longer changing its speed, though it may still be moving if the body has a constant speed associated with it.

Because acceleration is proportional to the net external force involved, and therefore more directly reflective of the energy costs, measuring PA using acceleration is preferred to using speed. From a technical standpoint, it is also more desirable to measure acceleration because it generates an information-rich signal that can be postprocessed into speed and distance signals using integration with respect to time, thereby conserving signal integrity that would be lost if

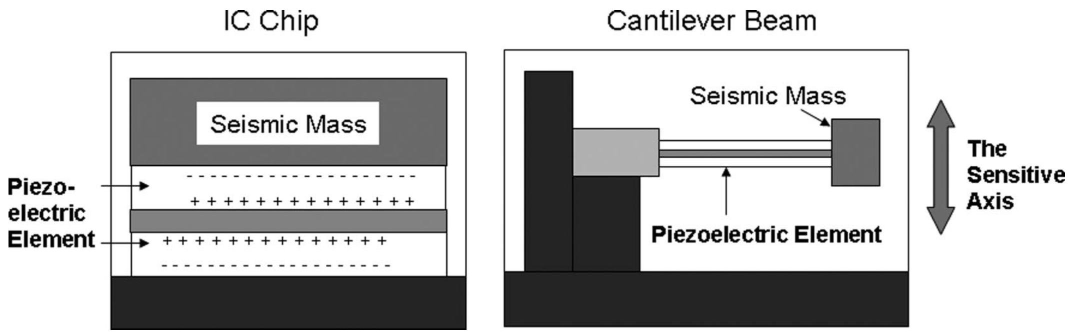

FIGURE 1—Schematic of the two common piezoelectric accelerometer configurations.

postprocessing was performed by differentiation with respect to time (53).

Piezoelectric sensor principles and properties. Most accelerometry-based PA monitors use one or multiple piezoelectric accelerometers. A piezoelectric acceleration sensor consists of a piezoelectric element and a seismic mass, housed in an enclosure (Fig. 1). When the sensor undergoes acceleration, the seismic mass causes the piezoelectric element to experience deformation in the forms of bending (in beam sensors) or direct tension or compression (in the newer integrated chip (IC) sensors). These conformational changes cause displaced charge to build up on one side of the sensor, which can generate a variable output voltage signal that is proportional to the applied acceleration. In the case of a beam configuration, the piezoelectric element is the most sensitive in the bending direction; hence it is often referred to as uniaxial. However, deformations in other directions or planes can also results in acceleration signals. Some define this type of piezoelectric sensor as omnidirectional, which means it senses accelerations not only in the axis of bending (e.g., vertical to ground), but also the other planes or directions (horizontal and lateral). Furthermore, the difference in sensitivity in each direction is determined by the geometry (cross-sectional area and length), material property (stiffness), and the positioning of the seismic mass on its beam. In fact, all piezoelectric beam accelerometers have various degrees of such omnidirectional effect. The output from these accelerometers combines signals from all directions, while the contributions from each direction are not differentiable.

To measure accelerations in multiple directions, several unidirectional translational accelerometer units must be mounted orthogonally to one another. This process can be performed either manually or through the use of a multiaxial IC accelerometer. Piezoelectric sensors are useful because they have high outputs for small strains and the potential of a large dynamic range (48).

A major limitation of most piezoelectric accelerometers is that they can only reliably be used to detect dynamic events. This is because of a phenomenon known as "leakage," which occurs when the initial change in charge in the piezoelectric element dissipates in time, even if the static loading that caused the initial change is still present. The rate at which leakage occurs depends on the time constant, a physical property of the piezoelectric material (48). The inability of most accelerometers to detect the static component of the acceleration means that they are not well suited for measuring the angles (with respect to gravity) of the attached surfaces and postures. In other words, they cannot detect body postures (standing vs sitting). However, recent advances in solid-state technology and digital filters have allowed the measurements of static acceleration and hence can provide information on body position.

Data acquisition, filtering, process, and storage. The rate of data acquisition is determined by the sampling frequency of the monitor computer. To ensure that the full range of human motions are captured independently, the sampling frequency should fulfill the Nyquist criterion (38), which specifies that the sampling frequency must be at least twice the frequency of the highest frequency of movement. If this criterion is not met, measurements of rapid motions (higher frequency domain) will be distorted. The general frequency in normal nonimpact PA of the center of mass in humans is below 8 Hz (during running in the vertical direction) (57); however, the upper limit could be as high as 25 Hz in specific movements of the arms. The sampling frequency for commercially available PA monitors thus generally range from 1 to 64 Hz.

After the data have been sampled, sensor output is filtered using a band pass filter. Band pass filtering allows frequencies between a preset low- and high-frequency limit to pass while all other frequencies are attenuated. This type of filtering increases the linearity of the output (measured acceleration) with respect to the true signal (body acceleration). The band pass filter also reduces the influences from artifacts such as aging of piezoelements or temperature-related sensor drifts, which are in the very low frequency domain (hours to months or $<$0.1 Hz) and electrical or electronic noise, which is in the higher frequency domain ($\geq$60 Hz). The currently used ranges by most commercial PA monitors are somewhere between 0.25 and 7 Hz. After passing the filter, the linearity is typically $>$0.98 (R^2) within a range of 1–2 *g* in most industry standard accelerometers. The limits of the band pass filter are also determined by the type of movement the device is intending to capture (50) and is generally in the range of 0.1–10 *g*. The acceleration components at the pelvis (vertical, anteroposterior, and mediolateral) generally range from 0.05–0.5 *g* during level walking (1–5 $m \cdot s^{-1}$), even after considering the variability in irregular surfaces (SD of 0.3 *g*) (32).

The selection of an appropriate frequency response range for a bandwidth filter could be significant. An overly wide bandwidth would allow noises that are not physiologically related (baseline drift or the hardware, vibrations such as operating a motor vehicle, or electrical artifacts) to be included in the signals. On the other hand, a narrow bandwidth could cause incomplete data collection of all activities. It has been reported that several currently available PA monitors are not as sensitive to activities that are of less than moderate intensities (20,47), and plateau in vigorous intensities (4,27).

What is a "count"? The raw outputs of accelerometers in PA monitors are known as counts. However, it is often unclear what a count truly means, physically or physiologically.

The initial signals for most accelerometry sensors are bidirectional. In other words, they can be positive and negative. This voltage signal, after being filtered and amplified (in most cases), is then sampled at a prefixed frequency by the device to convert the analog voltage signal to a digital series of numbers (A/D conversion), which are called "raw counts." The amplitude of this digital signal (raw counts) is determined by the system hardware including the analog voltage, the amplification factor, and the A/D conversion factor. In a common 8-bit conversion, each point signal's amplitude (raw counts) can range from -128 to $+128$ ($2^8 = 256$). However, these are not the same counts as the output of the current PA monitors. After these digital data strings reach the processor (microcomputer chips), different analytical approaches can be applied. The first approach is to use a digital counter to accrue the number of times the signal crosses a preset threshold. This threshold could be a value of zero (often referred as the zero-crossing method) or a "significant" value that is thought to represent motion. The second approach is to use an algorithm that can determine the maximum value for a selected time period (epoch) to represent the count for that time window. The third and most commonly applied method is to use the area under the curve (integration or average) algorithm.

Before the integration algorithm, the steps of the digital signal processing normally include converting the negative counts into positive ones (full-wave rectification, more common, Fig. 2) or taking only the positive side (half-wave rectification). This is to ensure that the integration does not include both positive and negative counts. The digital integration algorithm then sums the "raw counts" for each given time window (normally 1 min). The end result is often called the PA counts from each accelerometer.

The advantages of using the integrated signals include the simplicity for general understanding, the ease of processing for both hardware and software needs, and statistical robustness (integrated algorithm). However, the use of such processing techniques to extract PA measurements does have significant limitations. First, the integration process diminishes the details of the signals within each time window. The common duration for such time windows, at least in adults, is 1 min. However, it should be recognized that the time period over which accelerometer counts are averaged

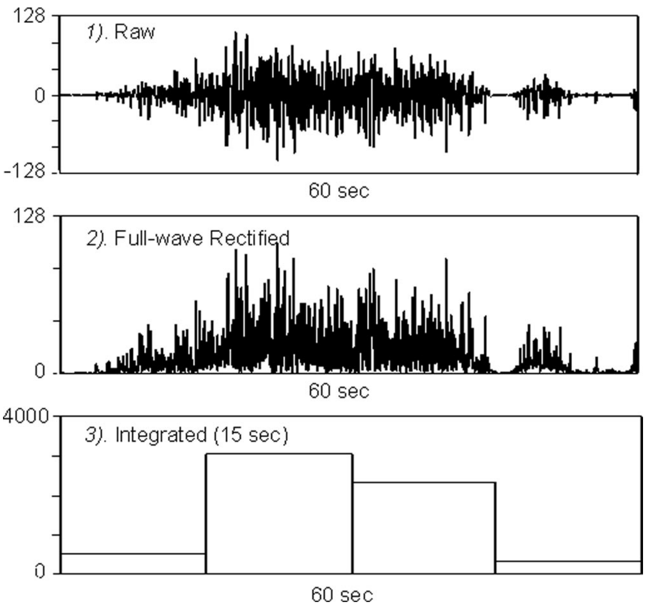

FIGURE 2—Analytical processing of the acceleration data. 1. Raw: a 60-s window of a digitized raw signal collected at 32 Hz and using a 8-bit A/D conversion. 2. Rectification: all negative signal from (1) was turned into positive. 3. Integration: 15-s epochs.

(termed an epoch) can affect the interpretation of data. Choosing a short epoch yields higher resolution of bout durations, which may be important if PA is accumulated in multiple short bouts. On the other hand, a disadvantage of short epochs is that the EE associated with 10- to 30-s epochs has little physiological value. Choosing a longer epoch has the normal data-smoothing advantage of time averaging. The main drawback is that if a long epoch contains a mixture of two activities of different intensity, then the data will be averaged to reflect an intermediate intensity. If the bout of a higher intensity PA within a particular epoch is shorter than the width of the epoch, the averaged PA count for the epoch will be lower than the actual PA intensity. This can lead to misclassifying higher intensity PA that are more intermittent into moderate or light categories. Thus, there is a trade-off between choosing shorter versus longer epochs. For most applications, 1-min epochs appear to be a reasonable compromise.

The detailed signal characteristics could be crucial to assessing PA types and intensities. Figure 3 demonstrates some clearly different signal patterns: the first set of signals simulates a consistent but low-intensity level of PA, the second a moderate-intensity PA over a period of time (or a bout), and the third a sporadic but higher intensity PA. However, the integrated outputs for these three signals for this time window are identical. No current standard currently exists for the units of PA counts across device manufacturers. As mentioned before, these are arbitrary parameters that depend on the A/D conversion, sensors, and amplification factors and are thus less physically meaningful in relationship to PA, particularly to the intensity or type of PA.

Reliability issues. The measures of intra- and intermonitor coefficients of variance (CV) and intraclass corre-

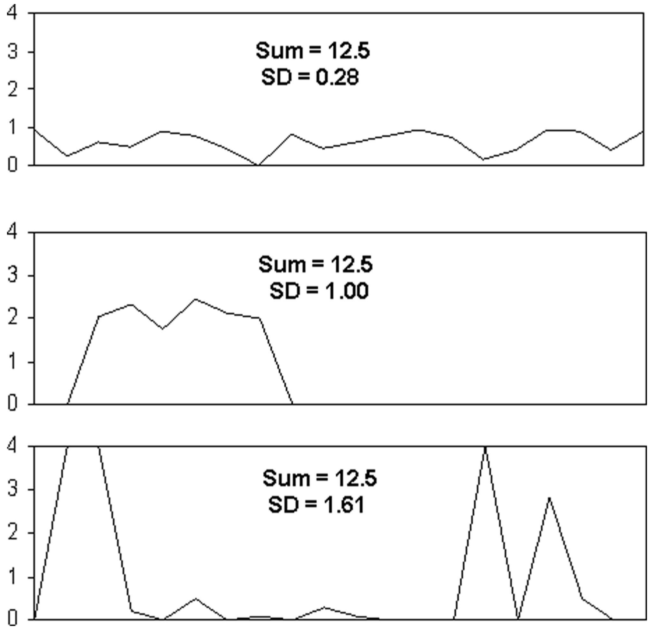

FIGURE 3—Three sets of arbitrary data vectors (20 points each) with the same digital integrated output, but very different SD.

lation coefficient (ICC) are normally used to define reliability in accelerometers. Reliability studies can be done using a calibration device (mechanical apparatus) with the advantages of better standardization and wider signal range. Alternatively, human trials can offer more "real-life" conditions. Welk et al. (54) have reviewed these issues in detail.

CURRENT TECHNOLOGY

Montoye et al. (34) were the first to recognize the potential of accelerometers to assess of the intensity of PA objectively. Currently used accelerometry PA monitors can be separated into two generations. The first generation consists of a single accelerometer placed on the waist (the most common position because it is closest to the center of body mass) or on an ankle or wrist. The Caltrac, Tritrac-R3D, RT3, ActiGraph, Actical, and Actiwatch are just a few commonly used PA monitors that are currently available for purchase in the United States. The technical and practical specifications of the currently marketed first generation PA monitors also are included in Table 1. The following provides a detailed description of those first generation PA monitors that have appeared most frequently in the published literature.

ActiGraph, formally known as Computer Science and Applications (CSA) and Manufacturing Technology Inc. (MTI) (ActiGraph, LLC, Fort Walton Beach, FL), is a uniaxial accelerometer device (51 × 41 × 15 mm, 43 g with a watch battery). The sensor is configured as a cantilever beam and is most sensitive in the vertical direction. It is waterproof. The manufacturer also makes a calibration device that is similar to a rotating shaker. If the calibration for a specific unit exceeds the preset sensitivity range, the user can manually adjust the unit by changing the hardware setting under the enclosure. The standard ActiGraph model 7164 model has 64 kbyte of internal random access memory (RAM) for data storage of 22 d using a 1-min epoch. The newly available ActiGraph model 71256 increases the memory storage capacity by four times (256 kbyte RAM). The piezoelectric accelerometer has a dynamic range of 0.05–2.0 *g* with a frequency response between 0.25 and 2.5 Hz. The ActiGraph has a sampling frequency of 10 Hz. It has multiple configurations to allow attachments to the wrist, ankle, or waist. Multiple studies have been conducted to establish the calibration of the ActiGraph for predicting EE in adults and children. These studies are reviewed by Matthews (32) and Freedson et al. (18).

TABLE 1. Technical details of several commonly used accelerometry-based PA monitors.

	Actigraph (MTI/CSA)	RT3	Actical
Manufacturer	MTI	StayHealthy	Mini Mitter
Battery type	Coin Cell	1 AAA	Coin cell
Battery life	160 d	30 d	180 d
Epoch	1 s–10 min	1 s or 1 min	15 s–15 min
No. of axes	Uniaxial	Triaxial	Uniaxial
Sampling frequency	10 Hz	Unpublished	32 Hz
Frequency response	0.25–2.5 Hz	Unpublished	0.5–3 Hz
Intermonitor CV	4–5% (31–33)[a]	4–26% (40)[a]	4–19%[a,b]
ICC (55,56)	0.80	0.73–0.87	0.62

[a] Tested with a mechanical device.
[b] Unpublished data from our laboratory.

RT3 Triaxial Research Tracker (StayHealthy, Inc., Monrovia, CA), is built on the original Tritrac-R3D technology. It is the size of a pager (71 × 56 × 28 mm and weighs 65 g with one AAA size battery) and is worn clipped onto the waist. It uses piezoelectric accelerometers and measures motion in three orthogonal dimensions and provides triaxial vector data in activity units. The sensor range, sampling frequency, frequency response, and A/D converting resolution are proprietary. The manufacturer's software estimates a subject's resting EE using published equations and associated EE ($EE_{ACT,}$ or the absolute intensity of PA) using the vector magnitude of the activity counts and a proprietary linear regression algorithm. The RT3 is capable of collecting and storing data up to 8.5 d (for triaxial output data mode). The significant improvement in technology from the original Tritrac-R3D to the RT3 was the conversion from three hand-soldered piezoelectric beam sensors to a triaxial IC chip setting. This minimizes the interinstrument errors and the risks of beam failure. The original Tritrac-R3D monitor included a backup battery (coin cell) to ensure no data storage loss when the main battery (9 V) was either too low or taken out. However, this feature no longer exists on the RT3, which can cause data loss (particularly in pediatric applications). The RT3 (or Tritrac-R3D) is not waterproof and does not allow manual adjustments for sensitivity.

Actical (Mini Mitter Co., Inc., Bend OR) is the newest and the smallest uniaxial accelerometer (28 × 27 × 10 mm, 17 g with a watch battery). It is worn at the hip of the subject. This device can record PA counts for up to 45 d using a 1-min epoch. The sampling frequency is 32 Hz, and sensitivity is 0.01 *g*. It collects motions in the frequency range of 0.5–3 Hz.

Actiwatch (Mini Mitter Co., Inc., Bend, OR), the predecessor of the Actical, has been used extensively in sleep research. The technology for Actical and Actiwatch is very similar, except that the Actical has the sensor oriented to detect vertical acceleration, has narrower bandwidth (compared with 0.5–7 Hz in Actiwatch) filter, and integrates raw counts over the epoch (rather than taking maximum signal over 1-s range then integrating over the epoch for Actiwatch). Both the Actiwatch and the Actical are waterproof and do not allow the user to manually adjust its sensitivity settings.

Collectively, the advantages of this class of accelerometry devices include their small size and the fact that they are wireless, noninvasive, and minimally intrusive to normal subject movements during daily activities. Thus, they are easy to use for subjects and testers. Compared to uniaxial sensors, a triaxial accelerometer provides a theoretically more comprehensive assessment of the body movements, shown by its higher correlation with measured EE in adults (20,58) and in children (15,30,39). However, the current analytical approach of combining the three axes into one summarized outcome parameter may not take the full advantage of the three-dimensional data (12), as we demonstrate later. These monitors normally record the PA using a quantitative but arbitrary intensity scale (PA counts) over a relatively extended measuring period (minute-by-minute data for up to 28 d), which makes free-living PA monitoring more feasible. However, this generation of PA monitors also has some limitations: a) they selectively record movement of the specific part of the body to which they are attached, and thus differences in PA types are mostly indistinguishable or unmeasured, and b) PA counts over a predetermined time epoch may have limited power for predicting EE_{ACT} of a wide range of types and intensities.

EMERGING TECHNOLOGIES

Realizing the limitations of the waist-mounted PA monitors, several research labs and companies have set out to develop the next generation of monitors, which have implemented two separate strategies: a) they use multisensor arrays applied at different body segments and b) they combine accelerometry with physiological sensor(s) in a single-site device.

Multisensor accelerometers. The approach of multiple measurements at different body segments was shown by Swartz et al. (47) in combining two accelerometers (ActiGraph) at the wrist and hip to determine whether EE_{ACT} prediction improved using a bivariate regression equation. This resulted in a statistically significant but small improvement ($R^2 = 0.34$, $P = 0.002$) compared with a univariate regression model using the hip sensor alone ($R^2 = 0.32$). In some research and development labs, the accelerometer sensors were arranged in parallel arrays and positioned at different body segments (mainly the chest and thighs) to monitor the types of activities by postural identification (6,17,23,24,28,50,52).

The target application for many of these prototype PA monitors, which have been tested primarily in small research labs in Europe, was rehabilitation in patients with leg amputation, back surgery, and chronic heart failure; although some "able-bodied" subjects were sometimes used as controls, the number of subjects and the types of PA used for development and validation were generally small (7,8,51). This class of investigational accelerometry monitors has the potential to detect postural changes and slow motions, which were the main limitations of the first-generation waist-mounted accelerometry-based PA monitors. However, these multiple-site monitors contain several wires, are not available outside the developing labs, and are expensive, all of which make them difficult for investigators to validate or apply in their field research.

Recently, the Intelligent Device for Energy Expenditure and Activity (IDEEA, MiniSun LLC, Fresno, CA), a new microcomputer-based portable PA measurement device has become commercially available. The IDEEA monitor uses continuous movement data from miniature accelerometry sensors ($16 \times 14 \times 4$ mm, the size of a thumb nail, weighing <1 g) attached with hypoallergic tape at five sites (five total sensors): the chest (upper sternum), midthigh of both legs, and both feet. The scale of the sensors is $\pm 2\ g$. Three thin and flexible wires (outside diameter = 1.7 mm) connect the sensors to the minicomputer ($70 \times 54 \times 17$ mm, weighing 59 g, and powered by one AA battery) clipped at the waist belt. Up to 7 d of continuous raw data (32 Hz sampling rate) in eight synchronous channels (sensors on the chest and both feet are biaxial accelerometers) can be compressed using an advanced algorithm and then stored in the IDEEA computer (200-MB storage capacity). Because both RAM and flash memories are used, data can be accessed quickly but without the risk of loss even with no power from the battery.

The IDEEA was designed to measure the complex aspects of PA, particularly for accurately determining PA modes. In a recent study, Zhang et al. (59) reported that the IDEEA monitor correctly identified postures, leg movements, and gaits (98.5%). Pooled correlation between predicted and actual speeds of walking and running also was high ($r = 0.986$, $P \leq 0.0001$). In a subsequent paper, these authors also reported that the estimated mean EE from the IDEEA was accurate (>95%) compared to the measured values in a calorimetry chamber (60). Although a correlation coefficient value of 0.96 was reported, the SEE (defined as the SD of the difference between predicted and the criterion measures) was not reported from this study.

Devices that combine accelerometry with other physiological measurements. In the second approach, single-unit monitoring devices are being developed that combine accelerometer(s) with other physiological measurements, such as HR, temperature, and others. As long as accelerometers have been in use, HR monitors also have been used as a simple method of estimating PA, EE_{ACT}, and even total EE, based on a linear or close to linear ($R^2 = 0.5$) relationship between EE_{ACT} and HR throughout a wide range of aerobic exercise levels (29,46). However, using HR for PA assessment would require individually fitted curves (EE prediction), and controlling for various factors, including fatigue, state of hydration, body temperature, emotional state, and use of substances such as caffeine and ephedrine (26,37,58). Another disadvantage is that HR is not a good predictor of EE at low levels of PA (29). Investigators also have tried to combine HR with accelerometers (in separate monitors) and demonstrated significant improvements in prediction accuracy (35). The details of methods combining HR and accelerometry have been reviewed by Strath et al. (46) and Brage et al. (3). Combining acceleration with HR and other measurements in a single unit would simplify the processes of application and data download and synchronization. Two monitors of this approach are now available to researchers. However, the incomplete measurement of different PA types associated with the nature of one-site movement detection with this approach is not significantly improved over the first-generation monitors.

Recently, the Actiheart (Mini Mitter Co., Inc.) device has integrated their accelerometer (uniaxial) with an ECG signal process for the simultaneous detection of HR and body movements. The Actiheart monitor consists of a 33-mm (diameter) main sensor and a 7-mm secondary sensor connecting through a flexible wire (188 mm total length). It weighs 10 g and has an internal rechargeable battery. The published range for the acceleration sensing is $>2\ g$, with an 8-bit A/D resolution, and 32-Hz sampling rate. The ECG (two lead between the main and the secondary sensors) is collected at 128 Hz and uses the standard R-wave detection algorithm to calculate HR (35–255 bpm). The Actiheart sensor is attached to the subject's chest with two standard stick-on ECG electrodes and has a recoding time of 11 d using 1-min epoch. Brage et al. (3) have demonstrated that the Actiheart-predicted EE, from an accelerometer/HR model, was significantly more accurate than using either parameter alone.

The SenseWear Armband (Bodymedia Inc., Pittsburgh, PA) is another newly available monitor ($85 \times 54 \times 20$ mm, 85 g with an internal lithium-ion battery) that is contoured to be worn at the upper arm. The internal sensors include an accelerometry sensor, heat flux sensor, galvanic skin response sensor, skin temperature sensor, and a near-body ambient temperature sensor. The accelerometer in the armband is a two-axis accelerometer that uses a microelectromechanical sensor device that measures motion. A polysilicon spring supports a small mass that moves when subjected to external acceleration, namely, body movements. The scale for the sensor is $\pm 2\ g$ with an 8-bit A/D converter (256 counts at 3.66 mg per count). The sampling rate is 32 Hz and has 512 kbyte RAM of data storage. The manufacturer's software calculates a subject's EE_{ACT} using a proprietary algorithm that combines acceleration, heat flux, and other parameters. However, it is unclear what percentage of each parameter ($>$20 total possible output parameters) contribute to the prediction equation. The SenseWear is capable of collecting and storing data up to 5.5 d using a 1-min epoch. Jakicic et al. (21) recently found that the SenseWear armband (using its built-in algorithms) underestimated EE during walking, cycling, and stepping (6.9–17.7%), while overestimated EE during arm ergometer exercise (29%). This further illustrates the limitation of the single-site monitoring approach and underlines the importance of better analytical development for the EE prediction models.

Shoe and ankle-mounted accelerometers. Although the accelerometers are primarily used in research, it is worth knowing that they may also be used to improve step counting and speed assessments during walking and running for the consumer market. Several large commercial companies (Nike Triax and Polar S1 foot pod) and developing companies (FitSense FS-1 and Dynastream AMP331) have incorporated the accelerometers in their products. The technical basis of these products is to measure the acceleration of the foot (by attaching the sensor to the shoe lace or ankle) and analyze the pattern of the movement (walking vs running) to estimate stride lengths and frequency. Signals are stored internally within the device (AMP 331) or transmitted through radiofrequency signals to a specially designed watch for speed display, storage, or combining with HR (FitSense, Nike Triax and Polar) to calculate energy cost. These devices are mostly downloadable to a computer for *post hoc* analyses.

Conger et al. (13) found that the FitSense device provides a reasonable estimate of speed and distance in level walking and running (for speeds ranging from 4.8 to 11.2 $km \cdot h^{-1}$). This is impressive given that most devices (e.g., waist-worn pedometers and accelerometers) cannot do that. Drawbacks of the FitSense speedometer were that it did not work well during uphill running, and it underestimated EE in the transition between walking and running. A preliminary study by Karabulut et al. (personal communication) examined the validity of the AMP 331 ankle-mounted accelerometer for measuring walking. The AMP was accurate for counting steps over a range of walking speeds from 40 to 107 $m \cdot min^{-1}$, though it consistently underestimated distance by a small amount. It also was insensitive to most sources of error, such as heel tapping, stationary cycling, and car driving. The FitSense speedometer and AMP 331 show promise for estimating EE of human gait patterns. However, the validity of ankle- and shoe-mounted accelerometers in nonwalking or running PA needs be further investigated.

ANALYTICAL APPROACHES TO PREDICTING EE

The four principal characteristics of PA are intensity, type, duration, and frequency. The absolute intensity of PA is defined as its EE_{ACT}. Many investigators thus use the minute-to-minute EE_{ACT} values predicted from the accelerometers to classify daily PA into intensity categories, bordered by cut points, to enable the duration and frequency of light, moderate, and vigorous PA to be recorded. Thus, errors of EE_{ACT} prediction could lead to misclassification of duration and frequency of PA. The various outcome measures from the accelerometry (or the combinational) devices should be calibrated against well-measured EE_{ACT}, as it is discussed in detail by Welk (54). Furthermore, the validity of using different PA monitors to estimate the intensity categories of PA (in metabolic equivalents, or METs) in adults and children is reviewed by Matthews (32) and Freedson et al. (18). The technological developments in accelerometry devices also include advancements in analytical modeling approaches.

As the criterion measure, EE_{ACT} can be assessed using indirect calorimetry or the DLW techniques. Indirect calorimetry measures O_2 consumption and CO_2 production prospectively and with precision, from which the rate of EE ($kcal \cdot min^{-1}$) is determined by standard predictive models. EE_{ACT} during any time window can be readily obtained after removing the resting EE and summing the area under the curve. This method is the most appropriate for precise and detailed comparisons in a well-controlled environment, but does not sufficiently assess all activities of the daily living. DLW is based on the difference in the rates of turnover of H and O in body water. This is achieved by measuring CO_2 production and disappearance rates of the isotopes (^2H and ^{18}O) in urine, blood, or saliva (43–45). EE_{ACT} during the entire study period (7–28 d) is then resolved as total EE − resting EE − thermic effect of food. As the gold standard for measuring free-living EE, DLW provides an accumulative measure for the entire measurement period, but does not reveal the day-to-day variations in EE_{ACT} (42,44,45).

Linear approaches. Most validation studies in the literature have evaluated the correlation coefficient between the activity counts from monitors with the single accelerometer configuration and EE measured using indirect calorimeters (metabolic carts, portable metabolic units, or room calorimeter) or DLW. In several validation studies conducted in laboratory settings, correlation values between EE measured by indirect calorimetry and accelerometer readings ranged from 0.58 to 0.92 during various activities (1,2,5,9,12,19,20,22,32,37). Level walking showed the highest correlation with the waist-worn triaxial accelerometers, with the r as high as 0.99 (27). Using a room calorimeter, we have shown that the group ($N = 125$) correlation between measured daily EE_{ACT} and the vector magnitude of a triaxial accelerometer activity counts was 0.54 on a sedentary day and 0.74 on a day with some nonintense activity added (12). Inspired by the significant correlations, many (if not most) investigators and device manufactures have applied linear regression equations to the monitors' output (PA counts) as the predictive models for EE_{ACT}. The classic development of such linear correlation approaches was demonstrated by Freedson et al. (19) in a pooled ($N = 35$) sample of young subjects exercising on a treadmill at three different intensities while wearing a uniaxial ActiGraph monitor at the hip ($R^2 = 0.82$). A subsequent study (36) also used the regression equations developed individually during a walking trial (r = 0.77 for ActiGraph and 0.89 for Tritrac-R3D) and applied them to the signals from more habitual PA types (r = 0.59 for ActiGraph and 0.62 for Tritrac-R3D). It should be noted that the correlation values in many of these studies associated activity counts with EE for the study group rather than for each individual. Although this method is sufficient for answering the question regarding validity as a group, it often does not account for important between-individual variations. Furthermore, within individuals, a PA monitor could underestimate certain PA while overestimating others, such that the total sum of predicted EE_{ACT} ends up being comparable to the measured overall EE_{ACT}. In turn, this significant error would lead to misclassification of the other key characteristics of the PA—duration and frequency.

A limited number of studies have explored the correlations between longer term EE_{ACT} predicted by accelerometers and measured EE_{ACT} using DLW. In a 7-d study of 13 normal young women under free-living conditions, Leenders et al. (25) found that, although the average PA counts from the ActiGraph and the Tritrac-R3D both significantly correlated with EE_{ACT} measured by DLW (r = 0.45 and 0.54, respectively), their predictive equations underestimated EE_{ACT} by 59 and 35%, respectively. Ekelund et al. (14) also found a similar correlation (0.54) in a group of 9-yr-old schoolchildren between total PA counts from a ActiGraph monitor and a 14-d DLW-measured EE_{ACT}.

Waist-worn accelerometers underestimate the EE of free-living individuals for a number of reasons (1,20). Failure to detect the additional EE resulting from arm activity, standing posture, vertical work (i.e., stair climbing or uphill walking), pushing or pulling objects, carrying extra weight (e.g., book bags, computers), nonweight-bearing exercise (e.g., bicycling), and PA in water (e.g., swimming) contributes to the error. Finally, waist-worn accelerometers that measure vertical acceleration generally cannot detect increases in EE that occur at running velocities over 9 $km \cdot h^{-1}$ (4), and they underestimate the EE of activities that require rapid changes in horizontal acceleration, such as tennis (1). The major advantage of the linear regression approach is its simplicity. This means that the output from the accelerometers can be readily calculated into predicted EE_{ACT} using popular software such as a spreadsheet. However, a major limitation is that the accuracy of the linear regression approach significantly depends on the types of PA performed (1,16).

Nonlinear approaches. Mathematically, the linear model is a simplification of more general nonlinear models, in which either the power parameter(s) equal to one or the logarithmic function is used to convert the input-output parameters. Physiological evidence also may support the nonlinear relationship between acceleration of body movements and EE_{ACT}. For example, it has been demonstrated that the EE_{ACT} was nonlinearly associated with the speed of walking and stepping in healthy adults (10).

Chen et al. (12) demonstrated the advantages of using a nonlinear power model to predict EE_{ACT} using PA counts from the Tritrac-R3D. Briefly, the whole-room indirect calorimeter was used as the gold standard and a two-component (vertical and horizontal) power model was developed to translate each individual's activity counts from the Tritrac-R3D to minute-

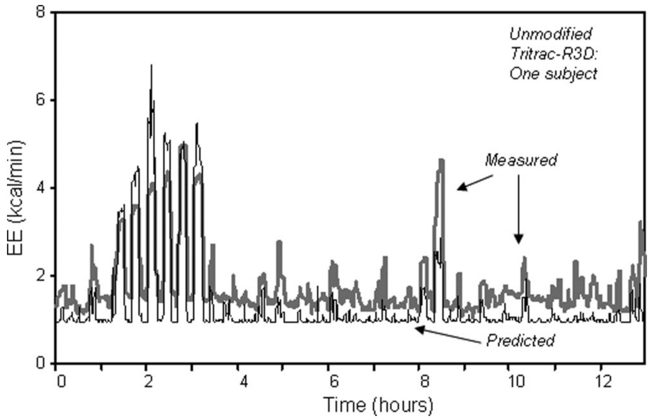

FIGURE 4—Subject: a woman age 32 yr, body mass 67.4 kg, resting EE = 1.06 kcal·min^{-1}. Tritrac-predicted EE (*thin black line*) vs the calorimeter-measured EE (*thick black line*) during the waking period of a 24-h stay in the room calorimeter. r = 0.88, SEE = 0.48 kcal·min^{-1}.

to-minute EE_{ACT} in a cross-sectional sample (N = 125) of heterogeneous normal men and women:

$$EE_{ACT} = a*(\sqrt{A_x^2 + A_y^2})^{p1} + b*A_z^{p2}$$

In this model, A_z represents the vertical acceleration counts, and counts in the A_x and A_y directions are combined to represent acceleration in the horizontal plane. The coefficients a, b, p1, and p2 were determined by a traditional unconstrained nonlinear optimization algorithm for each study individual. Compared with the manufacturer's prediction equation (linear model with vector magnitude of x, y, and z axes), this model's prediction of minute-by-minute EE_{ACT} was significantly improved in terms of correlation (r = 0.81–0.98, $P < 0.01$) and the SEE (0.35 ± 0.08 kcal·min^{-1}, $P < 0.001$). The improved prediction from the nonlinear two-component model was clearly evident for the same subject by comparing Figure 4 (Tritrac-R3D model) to Figure 5. For the group (N = 125), the model was able to improve the significant group underestimation of total EE_{ACT} from about 50% by the Tritrac-R3D model (Fig. 6) to about 3% (Fig. 7). Furthermore, this study was designed with two separate study visits for each subject, with

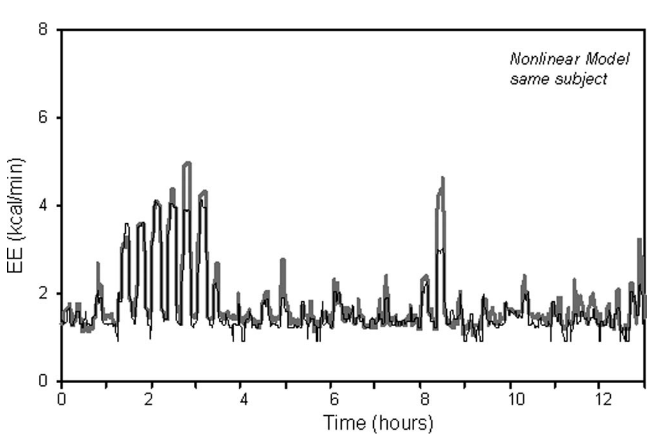

FIGURE 5—.Same subject as in Figure 4. Predicted EE using the modified two-component nonlinear model (*thin black line*) vs the calorimeter-measured EE (*thick black line*). r = 0.94, SEE = 0.27 kcal·min^{-1}.

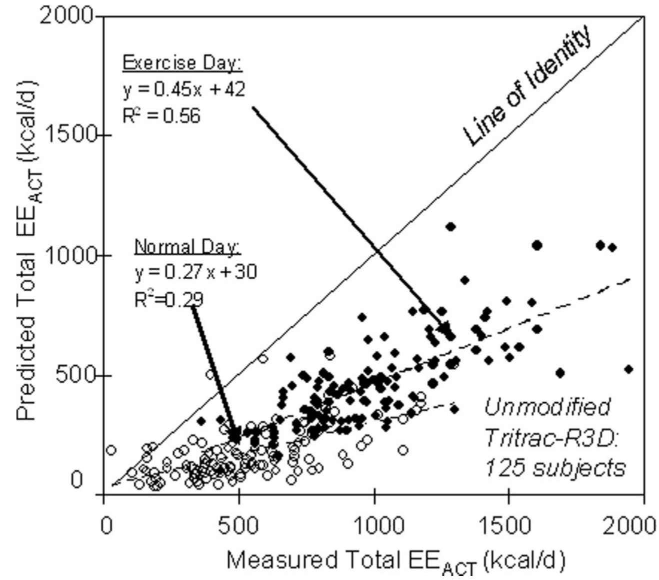

FIGURE 6—Calorimeter-measured vs Tritrac-predicted total EE_{ACT}. Group: 53 men, 72 women. The Tritrac-R3D underestimated (below the line of identity) total EE_{ACT}. The *open circles* represent the normal day and the *closed circles* represent the exercise day.

1 d randomized to include several 10-min moderate exercise bouts (denoted the exercise day) and the other day's PA was entirely spontaneous (the normal day). When apply the individual models developed from the exercise day were applied to the normal day Tritrac-R3D acceleration counts, the group prediction errors of total EE_{ACT} were also significantly improved. It could be further demonstrated that the individual models (N = 125) could then be generalized by using the multiple regression approach and reduced model coefficients (a, b, p1, and p2) to contain only the subject's gender and body weight without losing significant accuracy in predicting EE_{ACT} (12). The generalized results of the

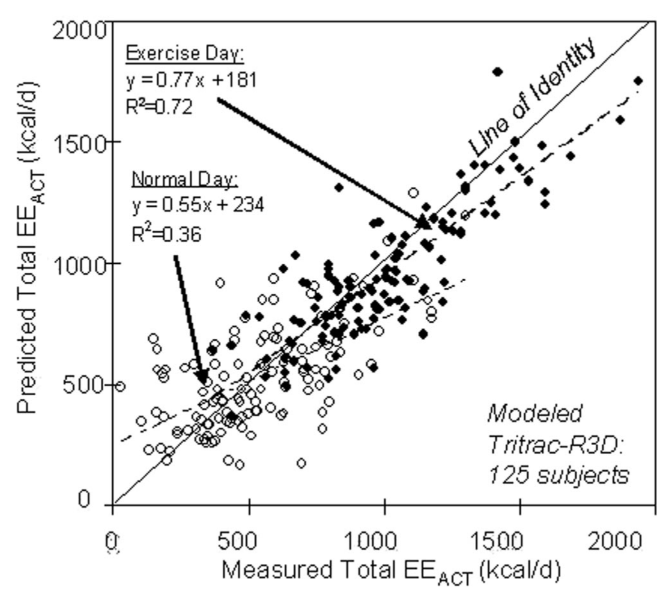

FIGURE 7—Same group as in Figure 6. Compared with the calorimeter-measured total EE_{ACT}, the two-component nonlinear prediction model significantly improved the estimation for the normal day and the exercise day. The *open circles* represent the normal day and the *closed circles* represent the exercise day.

power coefficients (p1 and p2) were both less than 1, suggesting the model tends to amplify the signals of light-intensity PA compared to PA of higher intensities. As an independent validation, Campbell et al. (9) applied this generalized model in a group of women during standard exercises (e.g., walking, jogging, stair climbing) and found significant ($P < 0.05$) improvement in EE_{ACT} prediction compared to the Tritrac-R3D models.

To follow this study, Chen et al. (11) have recently shown that this multicomponent power model approach to predict EE_{ACT} using accelerometer outputs could be extended to multiple devices. In a study of 60 healthy sedentary women, 24-h PA was measured by the same Tritrac-R3D triaxial accelerometer (worn at the hip) while adding a wrist uniaxial accelerometer (Actiwatch) on the dominant arm for simultaneous upper body movement measurements, in which the combined model was able to further improve the accuracy of predicting total EE_{ACT}. Comparing with modeling data from each individual, pooled sample data can be ascertained from a group where the prediction equation(s) can be derived for EE_{ACT} prediction. Puyau et al. (41) took a group of 32 children and developed a nonlinear predictive equation that associated ($R^2 = 0.74–0.79$ with the inclusion of weight, height, age, and sex) PA counts from two uniaxial monitors (Actiwatch and Actical, respectively) with measured EE_{ACT} during PA of various types and intensities. The advantage of the group model is its generalizability. However, it should be noted that the SEE (0.63–0.70 $kcal{\cdot}min^{-1}$) also were substantially greater than the individual models that we have shown previously. Thus, the group prediction model should be used with caution in individual EE predictions.

The major advantage of nonlinear modeling is its improved precision to predict EE_{ACT} in individuals and in groups. However, nonlinear models do have the tendency to be unstable (if the power parameter is >1) or to plateau too quickly (power parameter is <1) for higher intensity exercises. Our models (11,12) and those from Puyau et al. (41) all yielded to power parameters <1 . One solution to minimize the plateau effect is to design higher intensity exercises during model development stages. The other limitation of the nonlinear models is the computational complexity. However, with current and future technological advancements in microprocessors, this should be a minor concern.

Analyzing the variability in accelerometer counts. It is possible that analyzing the variability in accelerometer counts between several successive epochs may provide a closer estimate of EE than using counts alone. Bassett et al. (1) reflected on data from an earlier study. In that study, acceleration and EE data were collected for 28 different lifestyle activities falling into the general categories of lawn and garden, occupation, housework, family care, conditioning, and recreation. It was evident that uniaxial waist-mounted accelerometers (Kenz, Caltrac, and ActiGraph) overestimated the EE of walking, but underestimated the EE of virtually all other activities. Furthermore, it was possible to distinguish walking from other lifestyle activities because the variability in acceleration counts was less for walking than for other activities. Lifestyle activities such as gardening, vacuuming, sweeping, ironing, laundry, tennis, and golf are intermittent in nature and have more minute-to-minute variation in acceleration counts per minute than walking. This suggests a method whereby one might be able to improve on the estimation of EE by constructing two regression lines, one for walking and one for other activities.

SUMMARY

The role of PA in preventing and treating many chronic diseases has been recognized for some time, but improved methods of quantifying PA are now allowing us to refine our knowledge. Many instruments measure PA, and they vary by particular needs, feasibility, and accuracy. Small and wearable PA monitors, particularly accelerometers, are continually being refined as potentially very useful techniques in the accurate and detailed measurement of free-living PA.

Past and current research has mostly used waist-mounted accelerometers, which are compact, durable, and relatively inexpensive and have been proven reliable. However, the sensitivity and precision in determining the intensity of PA, particularly for the individual prediction of EE_{ACT}, need to be reexamined if they are to be used in clinical studies. Future accelerometry monitors must be designed to significantly improve their ability to predict EE_{ACT}. Moreover, in order to be portable and rugged enough for free-living applications, several crucial criteria should be followed: 1) they should be compact and contain no or a minimum amount of wires, and 2) they must have sufficient data-processing and storage capabilities to record continuous data for an extensive period. However, before all these criteria are realized in an ideal PA monitor design, careful studies must elucidate the components of raw accelerations that significantly contribute to the accurate predictions of EE_{ACT}. Crucial advancements in this process could lead to major improvements in determining not only the optimum data-processing algorithms, but also optimum sensor placement. Hypothetically, rather than using the time-averaged signals from a hip sensor, a combination of parameters that represent the high-frequency components of the arms (for upper body movements during sedentary PA), a postural parameter extracted from the chest that represents locomotion and intensity components extracted from leg movements can be uniquely combined to generate a significantly more accurate EE_{ACT} prediction.

In addition to the approaches presented here, advanced modeling techniques could also be used to develop accurate methods to link accelerometry output with EE_{ACT}. Particularly, with multidimensional measurements in body acceleration and other physiological parameters that are possible to collect using the emerging technologies, the nontraditional deterministic techniques may be more efficient to yield more reliable and consistent results.

For example, the artificial neural network (ANN) approach is a powerful information-processing paradigm inspired by the way the densely interconnected parallel structure of the mammalian brain processes information. An ANN is a collection of mathematical models that emulate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning. By systematically adjusting the "weights" applied to the multiple input parameters (e.g., acceleration signals) according to the overall prediction error compared to the target criterion (e.g., measured EE_{ACT}), this approach can help guide us to develop improved prediction models. This analytical framework can also be used to determine the optimum parameters from raw acceleration signals, other than the integrated PA counts, that are more suitable for the accurate prediction of EE_{ACT}. Thus, these types of research approaches could have the potential to guide the future designs of the accelerometry-based activity monitors, both in their hardware (sensors), software (models), and applications (location of wear). However, the main limitation of the ANN is the complex and "black-box" nature, thus are not readily implemented in current portable activity monitors with unsophisticated microprocessors. Advances that will allow researchers to deconvolute these models and generalizing them for such applications will be crucial to the success of implementing such approaches in accelerometry-based activity monitor designs.

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