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Assessing Physical Activity Using Wearable Monitors: Measures of Physical Activity

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ABSTRACT

BUTTE, N. F., U. EKELUND, and K. R. WESTERTERP. Assessing Physical Activity Using Wearable Monitors: Measures of Physical Activity. *Med. Sci. Sports Exerc.*, Vol. 44, No. 1S, pp. S5–S12, 2012. **Background**: Physical activity may be defined broadly as "all bodily *actions* produced by the contraction of skeletal muscle that increase energy expenditure above basal level." Physical activity is a complex construct that can be classified into major categories qualitatively, quantitatively, or contextually. The quantitative assessment of physical activity using wearable monitors is grounded in the measurement of energy expenditure. Six main categories of wearable monitors are currently available to investigators: pedometers, load transducers/foot-contact monitors, accelerometers, HR monitors, combined accelerometer and HR monitors, and multiple sensor systems. **Best Practices**: Currently available monitors are capable of measuring total physical activity as well as components of physical activity that play important roles in human health. The selection of wearable monitors for measuring physical activity will depend on the physical activity component of interest, study objectives, characteristics of the target population, and study feasibility in terms of cost and logistics. **Future Directions**: Future development of sensors and analytical techniques for assessing physical activity should focus on the dynamic ranges of sensors, comparability for sensor output across manufacturers, and the application of advanced modeling techniques to predict energy expenditure and classify physical activities. New approaches for qualitatively classifying physical activity should be validated using direct observation or recording. New sensors and methods for quantitatively assessing physical activity should be validated in laboratory and free-living populations using criterion methods of calorimetry or doubly labeled water. **Key Words:** PEDOMETERS, LOAD TRANSDUCERS, ACCELEROMETERS, HR MONITORS, MULTIPLE SENSORS

Physical activity is conventionally defined as "any bodily *movement* produced by the contraction of skeletal muscle that increases energy expenditure above a basal level" (51). In the field of physical activity monitoring, investigators have been interested in capturing the broad range of human behaviors encompassing "activity" and "inactivity." Physiologically, skeletal muscular contractions can be classified according to either length changes or force levels as concentric, eccentric, or isometric (static) (58). In many activities, all three types of muscle action may occur in the execution of a smooth, coordinated movement. For instance, resistance training can use isometric action, dynamic action, or both; static holds occur during standing, yoga, or martial arts. Therefore, physical activity may be defined more broadly as "all bodily *actions* produced by the contraction of skeletal muscle that increase energy expenditure above basal level."

In this article, we will review the basic construct underlying the assessment of physical activity using wearable monitors. We will identify components of physical activity that we currently can measure, as well as components that we would like to measure but that require more development of sensors and/or analytic techniques. The strengths and weaknesses of available monitors will be reviewed. Lastly, we will make recommendations for best practices and project future directions in the field of physical activity assessment. This review may be useful for engineers and device developers, measurement scientists, and end users who apply devices in health and behavioral research.

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CONSTRUCT UNDERLYING THE ASSESSMENT OF PHYSICAL ACTIVITY

Physical activity is a complex construct that can be classified qualitatively into major categories of sedentary behaviors, locomotion, work, leisure activities, and exercise. It also can be classified quantitatively by frequency (number of physical activity events in a specific period), duration (amount of time), and intensity (physiological effort). In addition, it

can be classified contextually by dimensions of time and place, position, or posture. In general, the field of activity measurement using electronic wearable monitors is more advanced in the quantification than the qualification (classification) of physical activity. The measurement of contextual factors of physical activity is just beginning.

The quantitative assessment of physical activity using wearable monitors is grounded in the measurement of energy expenditure (EE). Devices are calibrated and validated against EE measurements made by calorimetry or the doubly labeled water method. Total EE (TEE) is commonly partitioned into basal metabolic rate (BMR), resting metabolic rate (RMR), sleeping metabolic rate (SMR), thermic effect of food (TEF), and physical activity EE (PAEE) (21). BMR reflects the energy needed to sustain the metabolic activities of cells and tissues and the energy needed to maintain blood circulation, respiration, and gastrointestinal and renal function. BMR measurements are made on participants in a postabsorptive state and resting comfortably, supine, awake, and motionless in a thermoneutral environment. RMR tends to be somewhat higher (10% to 20%) than BMR because of increases in EE caused by recent food intake or physical activity. SMR is approximately 5% to 10% lower than BMR. TEF or the EE associated with the digestion and assimilation of food is determined primarily by the amount and composition of the foods consumed. PAEE, the energy above BMR, is calculated as TEE − BMR − 0.1TEE, assuming that the TEF for a mixed diet is equal to 10% of TEE and measurements are performed on participants in the fed state.

Of all the components of TEE, PAEE is the most variable among free-living individuals. Whereas BMR is mainly a function of body size and body composition and TEF is a fixed value, PAEE varies greatly among individuals. In the general population, physical activity level (PAL), computed as TEE/BMR, is between 1.2 and 2.2 to 2.5 (16). As a proportion of TEE, PAEE varies from 5% in a participant with a minimum PAL of 1.2 to 45%–50% in a participant with a PAL of 2.2–2.5 (55) (Fig. 1). At a PAL value of 1.75, close to the average reported for European, North and Central American, African, and Asian adults (57), PAEE represents 33% of TEE.

In kinesiology, metabolic equivalents is widely used to express the energy costs of physical activity as multiples of RMR. By convention, 1 MET is taken to be an oxygen uptake of 3.5 $mL \cdot kg^{-1} \cdot min^{-1}$ or 1 $kcal \cdot kg^{-1} \cdot h^{-1}$ in adults, a value derived for a 70-kg man age 40 yr (8). Between 1983 and 2005, RMR was measured in 366 adults in Maastricht (57). Average values for RMR were lower than 3.5 $mL \cdot kg^{-1} \cdot min^{-1}$, with women having slightly lower values than men as expected from the relatively larger metabolically inactive fat mass in women. Individual values showed a more than twofold range for participants differing in body size, with lower values for obese participants and higher values for lean participants. The conventional MET value is not applicable to children (37). When calculating PAL, the use of the conventional value for 1 MET, which is equal to 3.5 $mL \cdot kg^{-1} \cdot min^{-1}$ or 1 $kcal \cdot kg^{-1} \cdot h^{-1}$, is strongly discouraged for both adults and children. If measured values are not available, predicted BMR or RMR values can be used to appropriately adjust for individual differences in body size by expressing TEE as a multiple of BMR or RMR.

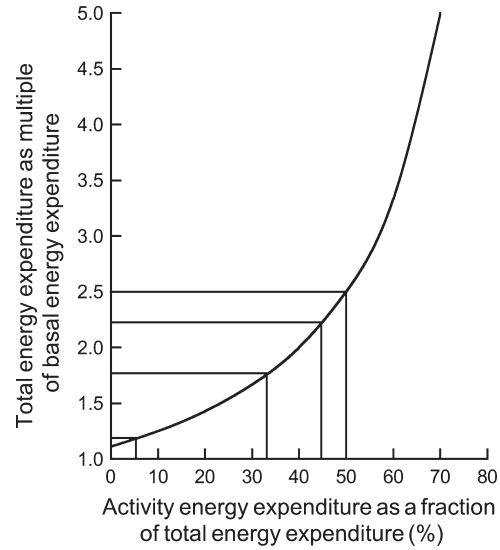

FIGURE 1—PAL, defined as TEE/basal EE, in relation to the fraction (%) of TEE in activity EE. The *rectangles* denote the figures for the minimum activity level (1.2 and 5%), average activity level (1.75 and 33%), and maximum activity level (2.2–2.5 and 45%–50%) (55).

Appropriate normalization of EE data for body mass is critical for understanding variability in basal metabolism and the energy cost of physical activities because body mass is the major predictor of EE. Theoretical, physiological, and mathematical arguments that support or dispute different approaches for the normalization of EE for body mass have been made (2,26,36). Constant ratio models (i.e., $kcal \cdot kg^{-1}$) are commonly used in many applications, but they do not take into account nonlinearity and thus fail to produce a variable independent of body weight (26,36). Tanner (46) showed that the mathematical bias may lead to spurious conclusions when individuals who vary in body size are compared using the ratio method. Linear regression models are an improvement but can create positive and negative biases. Linear models assume an additive error term, which is questionable because rates of EE diverge with an increase in scale. Inspection of EE data versus body weight reveals a curvilinear relation with a strong linear component, and these issues need to be taken into account in selecting empirical models to adequately explain the underlying data. Thus, a considerable amount of flexibility for fitting EE data can be gained by considering a nonlinear model (42). Recently, Davies and Cole (14) advocated power function models to investigate the adjustment of measures of EE for body weight and body composition. The curvilinear power function model between physiological variables and body mass has had a long tradition in physiology and has been shown to be superior to linear models (25). For instance, van Hees et al. (52) demonstrated that the square

root of body weight was appropriate for adjusting PAEE for differences in body weight.

To establish the relationship between PAL or PAEE and health outcomes, determination of reference values is needed. Doubly labeled water studies have provided the PAL reference ranges for adults and children. Reference PAL values for children show a gradual increase to reach adult values by about the age of 15 yr (Fig. 2). With increasing age, relatively less energy is required for maintenance, whereas the costs of physical activity increase as a function of increased body mass (15,19). Consistent with changes in PAL as measured by wearable monitors, PAEE per kilogram of body weight declines with age (15). The activity pattern of children is characterized by short intermittent bouts of physical activity (20), compared with the more deliberate activity patterns in adult and elderly persons (30,54).

Apart from subject characteristics of age, sex, weight, and height, measures of physical activity can make a significant contribution to the prediction of EE. In a review article, eight motion devices were evaluated against the doubly labeled water method, which measures TEE (34). The contribution of acceleration to TEE varied considerably; partial correlations ranged from 0.18 to 0.79. Clearly, activity monitoring can partially explain interindividual variation in levels of TEE. However, individual characteristics cannot explain intraindividual variation in EE throughout the day because these parameters are constants. In a cross-sectional time series model, Zakeri et al. (59) evaluated the contribution of individual characteristics, HR, and physical activity to the prediction of minute-to-minute EE. The cross-sectional time series model, based solely on the HR and physical activity, explained 72% of the variability in minute-by-minute EE within individuals compared with 90% when the model included individual characteristics, HR, and physical activity.

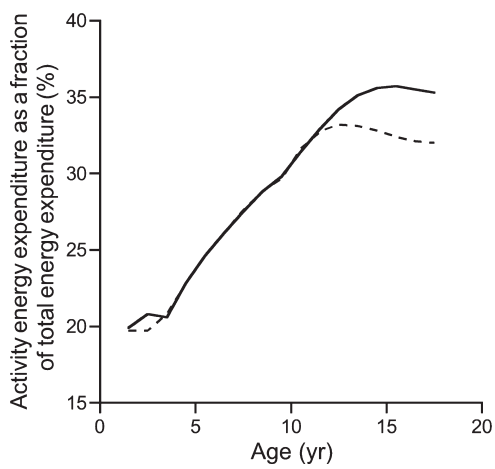

FIGURE 2—Activity EE as a fraction of TEE in relation to age for boys (*continuous line*) and girls (*broken line*) based on data in the Food and Agriculture Organization/World Health Organization/United Nations University Expert Consultation on Human Energy Requirements (16).

CURRENT TECHNOLOGY

The components of physical activity that we are currently able to measure with monitors with varying levels of accuracy and precision include the following:

1. Total physical activity
2. Duration, frequency, and intensity of physical activity
3. Sleep and awake time
4. Sedentary, light, moderate, and vigorous levels of physical activity during awake time
5. Prediction of TEE, PAEE, and SMR
6. Classification of locomotive activities (walking, jogging, running)
7. Walking (number of steps, stride, speed, distance)
8. Posture (lying, sitting, standing)

In addition to improving the measurement of the components of physical activity listed above, the field would advance with further development of sensors and analytic techniques for the following:

1. Classification of physical activity modes
2. Energy cost of specific physical activities
3. Contextual information (where, when, and with whom physical activity occurs)
4. Automated detection of nonwearing time and awake/nap/night sleep times

Several monitors are available to measure physical activity. The selection of the assessment tool depends on the physical activity component of interest, study objectives, characteristics of the target population, and feasibility in terms of cost and logistics. Physical activity monitors have been used in studies addressing obesity prevention and treatment, sports, fitness and performance enhancement training, other health outcomes (osteoporosis), sleep disorders, and rehabilitation involving gait and locomotion. The main categories of wearable monitors for assessing physical activity are as follows:

1. Pedometers
2. Load transducers (also known as foot-contact monitors)
3. Accelerometers
4. HR monitors
5. Combined accelerometer/HR monitors
6. Multiple sensor systems

Pedometers. Pedometers are small, lightweight, portable, noninvasive, nonintrusive, and inexpensive devices that use three primary mechanisms: a spring-suspended horizontal lever arm, a magnetic reed proximity switch, and piezoelectric uniaxial, biaxial, and triaxial accelerometers (5). Many pedometer models are available, and variability exists not only in cost but also in mechanism, data storage, and sensitivity. Pedometers are most accurate at step counting, less accurate in distance estimates, and even less accurate at estimating EE (43). Some pedometers measured steps within 3% of actual values, while others were within ±37% (43). Those that allow stride length to be entered and provide distance estimates are

reasonably accurate at normal walking speeds but overestimate at slow speeds and underestimate at high speeds. Pedometers can be valuable tools for continuously monitoring ambulatory activity, but it is imperative that investigators determine the accuracy and reliability of the pedometers they intend to use.

Weaknesses of pedometers include no recording of horizontal or upper body movement, insensitivity to gait differences such as stride length that varies with activity type, and limited validity of EE estimation. In addition, the outputs of all pedometers are not comparable.

Load transducers. Electronic load transducers or foot-contact monitors have been used to measure walking activity or loads held, lifted, or carried (17). Shoe- and ankle-mounted devices measure the acceleration of the foot and analyze patterns of movement, stride lengths, and frequency and estimate speed and distance of level walking and running. These devices have not been validated for habitual physical activity.

Accelerometers. Accelerometers are small, lightweight, portable, noninvasive, and nonintrusive devices that record motion in one or more planes and provide an indication of the frequency, duration, and intensity of physical activity (10,12,23,53). Originally, devices used a horizontal cantilevered beam with a weight on it. When subjected to vertical acceleration, the beam flexes and compresses a piezoelectric crystal that generates a voltage proportional to the acceleration. Newer devices use integrated chip sensors that have a seismic mass that sits directly over a piezoelectric element. The raw acceleration signal is analog/digital converted, filtered, and rectified and summarized for discrete epochs. Current uniaxial and triaxial monitors are capable of recording physical activity during extended periods. The raw output from accelerometers is then calibrated to some meaningful indicator of physical activity or EE.

Validity studies have yielded moderate-to-strong correlations (r = 0.45 to 0.93) between accelerometer counts and oxygen consumption ($\dot{V}O_2$), PAEE, or MET in adults and similar correlations (r = 0.53 to 0.92) in children (50). The wide range of agreement is due, to a large extent, to the type of measurement protocol. Compared with uniaxial sensors, triaxial accelerometers theoretically provide a more comprehensive assessment of body movements. Triaxial accelerometers have been shown to have higher correlations with measured EE in adults and children than uniaxial accelerometers in some but not all studies (10,52,56). Most piezoelectric accelerometers can only reliably detect dynamic, not static events. New solid-state technology and digital filters can measure static acceleration and hence body posture.

Triaxial accelerometry provides a technique for quantifying movement patterns during walking (23). Normal walking patterns can be deduced from vertical and anterior–posterior accelerations, which coincide with step frequency and account for the majority of the total signal power in each direction. Mediolateral accelerations are governed by the stride frequency and also are useful for detecting gait abnormalities. Specific gait-related movement can be measured from hip, shoulder, upper trunk, thigh, and lower trunk accelerations.

Accelerometers have been used to partition awake time into sedentary, light, moderate, and vigorous levels of physical activity. For adults, light, moderate, and vigorous levels have been defined conventionally using the thresholds of 3 and 6 METs (3). No consensus exists on thresholds for children and adolescents. Thresholds have been derived mathematically from prediction equations at predetermined physiological values or statistically using receiver operating characteristic curves to minimize false-positive and false-negative classifications. The 80th percentile from the distribution of physical activity counts has been used to represent vigorous physical activity (22). MET or physical activity ratio values, computed using measured or predicted BMR or RMR, have been used by others (22,38,48). PAEE thresholds have been used as well (38,48). As a result, studies are conflicting regarding levels of physical activity in youth. Accelerometers also have been used to quantify the amount of time spent in sedentary behaviors. Sedentary thresholds have been determined by observation, statistically, and physiologically as MET values less than 1.5.

Weaknesses of accelerometers are the lack of industry standards for conversion of accelerometer raw output to counts, proprietary algorithms, and inability to distinguish different types of activities, especially nonambulatory and static activities such as cycling and weight lifting (29). Across the dynamic range from sedentary to vigorous physical activity, a more sophisticated modeling of individual vectors is needed to extract more information from uniaxial and triaxial acceleration signals.

HR monitors. HR monitors are lightweight devices that have been used to predict PAEE (9,28). On the basis of the linear relationship of HR to EE, the FLEX HR technique has been shown to be valid and reliable. Because of the overlap between active and sedentary HR, a threshold value of HR is used to discriminate PAEE from sedentary EE. Prediction errors of group means have been reported below 3%, sometimes without any significant difference from the reference method; however, the range of prediction errors for individuals was greater than 10% (9,28).

Weaknesses of these monitors are that HR is a poor predictor of EE in the range of low-intensity physical activity (PA), the FLEX HR technique requires individual calibration, data processing is laborious and time-consuming, wearing electrodes for extended periods may be logistically difficult and can cause some skin irritation, and HR is subject to other stimuli besides physical activity. It is important to note that a large proportion of the population is on prescription drugs that affect HR. These include β-blockers for high blood pressure and β2 stimulators for asthma. Calibration of the individual's HR-to-EE relationship would have to be performed under the influence of usual prescription drugs.

Combined accelerometer/HR monitors. Accelerometers and HR monitors have been combined to improve the accuracy and precision with which EE can be predicted.

In one approach, accelerometer data were used to assign HR to one of two linear regressions relating HR to $\dot{V}O_2$ (31,47). In another, accelerometers were used to discriminate between arm and leg movement, and EE was predicted from the corresponding arm or leg HR-to-EE regression equation (44,45). Brage et al. (7) used branched equation modeling of simultaneous accelerometry and HR monitoring to improve the estimate of PAEE. Zakeri et al. (59) developed cross-sectional time series models to predict EE from HR and accelerometer counts using the Actiheart (CamNtech Ltd, Cambridge, UK) monitor in children and adolescents. The prediction error was 0.9% ± 10.3% for TEE and 1.5% ± 8.7% for SMR with no systematic bias by sex, age, or weight status. In general, the combined accelerometer and HR monitor method has better accuracy and precision than either method alone. TEE, PAEE, and SMR have been predicted within acceptable limits from the combined approach. Further research is required to predict the energy cost of specific activities with an acceptable degree of accuracy.

Another application is the measurement of HR in combination with body movement as a measure of physical fitness (32,33). Those with a higher level of physical fitness can generate more activity at a lower HR than can unfit participants. Short observation intervals on the order of 1 d are sufficient to generate adequate information regarding physical fitness.

Multiple sensor systems. Systems that entail attaching multiple sensors to the body trunk and extremities have been developed. The Intelligent Device for Energy Expenditure and Activity (MiniSun LLC, Fresno, CA) system captures body and limb motions through five sensors attached to the chest, thighs, and feet (60,61). The system uses an artificial neural network to recognize 32 types of activities such as jumping, walking, running, and stair climbing and descending. In adults, the Intelligent Device for Energy Expenditure and Activity correctly identified posture and limb movement and gait 98% of the time (60,61). Energy costs of specific activities are assigned from a published compendium of physical activities that is available for adults (1) but limited for children (39). Another physical activity measurement system, developed for adults and children, incorporated inclinometers and triaxial accelerometers to capture body position and motion (27). Body posture was correctly identified, and accelerometer output correlated well with varying walking velocities.

Weaknesses of multiple sensor systems are that available systems are wired, not wireless, and therefore cumbersome and intrusive; systems are expensive; complex, sophisticated data processing is required; and limited validation studies exist across populations. Integration of multiple wireless sensors attached to the body, however, has great potential for future advances in activity monitoring.

EMERGING TECHNOLOGY

Mathematical models to classify physical activities. An emerging area in the field of activity monitoring is the classification of physical activity type using advanced modeling methods. Probabilistic artificial neural networks have been used to extract information on physical activity type, duration, and intensity (24,60,61). Quadratic discriminant analysis and hidden Markov modeling have been used to classify physical activity type (35). Because of intrinsic misclassification error, accelerometers are unable to distinguish correctly two activities that produce similar total acceleration over time but have different energy costs. Quadratic discriminant analysis uses the mean and data dispersion to classify physical activity type. Hidden Markov modeling is a probabilistic pattern recognition algorithm similar to artificial neural networks, but the autocorrelation built into the algorithm allows one to share classification strength across observations that are close together in time. Classifications based on quadratic discriminant analysis were 53% to 100% correct, and hidden Markov modeling was 62% to 99% correct (35).

Future development of these methods will require training hidden Markov modeling to recognize more activities and incorporating individual characteristics and environmental factors into the models. Classification of physical activity type is important for describing human behavior as well as EE prediction. In a recent study, a classification tree algorithm was used to classify acceleration into one of six activity classes in combination with standard MET values for each activity type, which resulted in improved prediction of TEE (6).

Global Positioning System. Contextual information (where, when, and with whom physical activity occurs) can complement the measurement of physical activity (40,49). A Global Positioning System (GPS) is a satellite-based system that can provide information on a person's location, neighborhood context, mode of transportation, and speed of locomotion. A pilot study showed a slight advantage of using GPS in combination with accelerometer data to classify physical activity type (49). GPS signals also can be coupled with geographic information system data for richer contextual information that provides spatial matching (e.g., exercising in a specific park, walking to nearby shops/restaurants for utilitarian purposes). The reliability and validity of GPS have been demonstrated in different environments. GPS and triaxial accelerometers are now embedded into cell phones. Cellular phone technology can be used not only to assess physical activity and location but also to motivate participants to comply with physical activity interventions through interactive individualized feedback.

The weaknesses of GPS include added participant burden; complexity of data collection, processing, and analysis; and equipment costs. An additional weakness of GPS is that it is limited to mostly outdoor activities with "visible" sky. This would limit positional capabilities in many situations, such as activities at home and in the workplace, school, shopping malls, and fitness facilities and transportation activities (e.g., walking to and fro that might occur in bus tunnels or subways). The Wi-Fi capabilities of mobile phones (triangulation) could complement GPS in these instances.

New modeling approaches. Oversimplification of the data analysis and modeling of a complex construct presents a significant gap in the field of physical activity measurement. For the most part, linear regression approaches have been used to predict EE from accelerometer output (4). Two-regression models also have been used (13,18). On the basis of the variability of physical activity counts within an epoch, a two-regression model for walking/running and other lifestyle leisure time activities improved the prediction of MET compared with a single-regression equation (13). Compared with the doubly labeled water method, the linear regression equations tend to underestimate free-living PAEE (34). Uniaxial accelerometers mounted on the hip or waist failed to detect EE from arm movement; standing posture; vertical work; pushing and pulling; carrying weight; non–weight-bearing exercise, such as bicycling or swimming; and rapid changes in horizontal acceleration, such as tennis. Triaxial accelerometers can address some of these shortcomings of uniaxial accelerometers.

Given the limitations of previous approaches, nonlinear approaches may be more appropriate for EE and physical activity prediction models. Chen and Sun (11) used a two-component (vertical and horizontal acceleration) power model to predict PAEE from accelerometer output. Puyau et al. (38) used a multicomponent power model to predict PAEE from accelerometers using weight, height, age, and sex. Rothney et al. (41) developed an artificial neural network model of EE using biaxial acceleration signals. Brage et al. (7) used branched equation modeling of simultaneous accelerometry and HR monitoring to improve the estimate of PAEE.

Mathematical modeling of the HR and accelerometer counts has been limited to regression models that do not take into account the interdependence of EE, HR, and counts over time. As a result, these methods have not exploited all the information in the raw data. To account for the interdependence of the data over time, Zakeri et al. (59) applied a cross-sectional time series analysis to predict EE from HR and accelerometry. This approach efficiently modeled the correlated data, taking into account within-individual changes and between-individual heterogeneity.

Another modern statistical technique, multivariate adaptive regression splines (MARS), has been applied to the prediction of EE from accelerometer and HR data (60). MARS is a multivariate nonparametric regression method. A major aspect of the nonparametric approach is that the complexity of the method will be determined completely by the data, thereby avoiding subjectivity in selecting a specific model. The MARS method approximates a complex nonlinear relationship by a series of spline functions on different intervals of the independent variable. MARS can be viewed as a generalization of binary recursive partitioning because it overcomes some of the limitations of recursive partitioning. In recursive partitioning, the subregions are disjointed, and as a result, the approximating functions are discontinuous at the subregion boundaries, which severely limits the accuracy of the approximation, in particular, when the underlying function is continuous. MARS has overlapping subregions, and it produces a continuous model for continuous predictors, which should improve prediction of EE from HR and accelerometry.

These advanced modeling techniques, which include recursive partitioning, cross-sectional time series analysis, MARS, and artificial neural networks, have the potential to improve population-specific prediction models for EE. Pattern recognition and machine learning techniques such as artificial neural networks, classification and regression trees, quadratic discriminant analysis, and hidden Markov modeling also hold promise for classifying physical activity.

BEST PRACTICES

Currently available monitors are capable of measuring total physical activity as well as components of physical activity that play important roles in human health. The selection of wearable monitors to measure physical activity will depend on the physical activity component of interest, study objectives, characteristics of the target population, and study feasibility in terms of cost and logistics. Currently, six main categories of wearable monitors are available to investigators: pedometers, load transducers/foot-contact monitors, accelerometers, HR monitors, combined accelerometer and HR monitors, and multiple sensor systems.

Because physical activity may be defined broadly as "all bodily actions produced by the contraction of skeletal muscle that increase energy expenditure above basal level," it is reasonable to express the output of measures of physical activity in terms of EE. For meaningful comparisons between persons or populations, absolute measurements of EE must be normalized appropriately for differences in body mass directly or indirectly using measures of basal metabolism. When calculating PAL, the individual's measured or predicted BMR or RMR should be used to adjust for individual differences in body size.

The use of wearable monitors to partition total activity into sedentary, light, moderate, and vigorous levels of physical activity has many useful applications in research, public health, and policy. However, the prediction errors of physical activity thresholds should be fully disclosed in publications and documents.

One cross-cutting issue is comparability between brands of wearable monitors for the measurement of the components of physical activity. Except for HR monitors, different brands of wearable monitors have no uniformity in output units. For instance, manufacturers report incompatible counts per unit time after undisclosed data processing of the raw accelerometer signal. Because all accelerometers measure acceleration ($m \cdot s^{-2}$), a consensus on filtering and reporting accelerometer values as the primary output would facilitate data comparisons across monitors.

FUTURE DIRECTIONS

Future development of sensors and analytical techniques for the assessment of physical activity should focus on the

dynamic ranges of sensors, comparability for sensor output across manufacturers, and the application of advanced modeling techniques for EE prediction and classification of physical activities. Contextual information using GPS and/or a geographic information system has potential for complementing the measurement of PA, especially if these instruments can be bundled with the motion sensors. New approaches for the qualitative classification of physical activity should be validated using direct observation or recording. New sensors and methods for the quantitative assessment of physical activity should be validated in laboratory and free-living populations using criterion methods of calorimetry or doubly labeled water.

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