Field Validation of the MTI Actigraph and BodyMedia Armband Monitor Using the IDEEA Monitor

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Abstract

WELK, GREGORY J., JAMES J. MCCLAIN, JOEY C. EISENMANN, AND ERIC E. WICKEL. Field validation of the MTI Actigraph and BodyMedia armband monitor using the IDEEA monitor. *Obesity.* 2007;15:918–928.

Objective: Accelerometers offer considerable promise for improving estimates of physical activity (PA) and energy expenditure (EE) in free-living subjects. Differences in calibration equations and cut-off points have made it difficult to determine the most accurate way to process these data. The objective of this study was to compare the accuracy of various calibration equations and algorithms that are currently used with the MTI Actigraph (MTI) and the Sensewear Pro II (SP2) armband monitor.

Research Methods and Procedures: College-age participants ($n = 30$) wore an MTI and an SP2 while participating in normal activities of daily living. Activity patterns were simultaneously monitored with the Intelligent Device for Estimating Energy Expenditure and Activity (IDEEA) monitor to provide an accurate estimate (criterion measure) of EE and PA for this field-based method comparison study.

Results: The EE estimates from various MTI equations varied considerably, with mean differences ranging from −1.10 to 0.46 METS. The EE estimates from the two SP2 equations were within 0.10 METS of the value from the IDEEA. Estimates of time spent in PA from the MTI and SP2 ranged from 34.3 to 107.1 minutes per day, while the IDEEA yielded estimates of 52 minutes per day.

Discussion: The lowest errors in estimation of time spent in PA and the highest correlations were found for the new SP2 equation and for the recently proposed MTI cut-off point of 760 counts/min (Matthews, 2005). The study indicates that the Matthews MTI cut-off point and the new SP2 equation provide the most accurate indicators of PA.

Key words: accelerometer, Actigraph, energy expenditure, pattern recognition, physical activity

Introduction

Accelerometry-based physical activity monitors provide objective data on levels of physical activity (PA)[1] and energy expenditure (EE) associated with physical activity (1). While accelerometers are commonly used in behavioral, clinical, and epidemiological research, there are many challenges that must be overcome to improve measurement accuracy. A recent conference highlighted the measurement issues that need to be resolved to improve the science of accelerometry (2). One of the fundamental challenges is to determine the most appropriate calibration equations and cut-off points for processing and reducing accelerometer data (2,3).

Developing accurate calibration equations with accelerometers has been challenging for several reasons. One factor is that individual differences in body size influence the movement counts associated with PA (4). Calibration equations have been shown to provide valid estimates for group-level comparisons, but these equations have not been shown to be accurate for individual-level estimates (1). Another factor is that the relationship between movement counts and EE is different for different activities. Equations based on locomotor activities have been shown to be accurate for walking but have been shown to underestimate the energy

Received for review January 23, 2006.
Accepted in final form October 20, 2006.
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The authors dedicate the paper in memory of their colleague, Dr. Paul Flakoll, who provided access to (and insight on) the use of the IDEEA monitor for this study.
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[1] Nonstandard abbreviations: PA, physical activity; EE, energy expenditure; SP2, Sensewear Pro II; MTI, MTI Actigraph; IDEEA, Intelligent Device for Estimating Energy Expenditure and Activity; MVPA, moderate to vigorous physical activity.

cost of household or lifestyle tasks by as much as 50% (5,6). While some researchers have developed algorithms to more accurately capture the energy cost of lifestyle activities (7,8), these equations tend to overestimate the energy cost for free-living activity (9,10).

The purpose of this study is to examine the accuracy of EE equations and PA cut-off points for a widely used accelerometer (the MTI Actigraph; MTI) and a relatively new armband monitor (Sensewear Pro II; SP2) under field conditions. Although the MTI has been used in a variety of research applications, there remains considerable confusion about which equation/cut-off point provides the most accurate estimate of PA and EE for free-living adults (4,11). The SP2 is a multichannel body monitor that relies on a pattern recognition approach for EE and PA estimation. Several studies have demonstrated the utility of the Sensewear Pro Armband (12–14), but findings with the latest algorithms (version 4.0/4.1) have not been reported. The SP2 has also not been systematically compared against other measures under free-living conditions.

An inherent challenge in validation research with accelerometers has been the lack of an appropriate criterion measure of EE and PA for field-based research (1,4). The present study uses the Intelligent Device for Energy Expenditure and Physical Activity (IDEEA), which uses a series of electrodes and a complex neural network to determine the predominant postures and motions that are being performed. Recent studies have demonstrated that the IDEEA can accurately detect most fundamental movement patterns (15) and produce highly accurate estimates of EE (16). Because this device can process data by time and be worn during free-living conditions, it provides an effective tool to evaluate other accelerometry-based monitors.

Research Methods and Procedures

Participants

The participants in the study were 30 college-age males ($n = 13$) and females ($n = 17$) from a large university in the midwestern United States. The study was approved by the Institutional Review Board, and all participants signed informed consent documents after an explanation of the purpose and procedures of the study.

Instruments

IDEEA Monitor

The IDEEA monitor (MiniSun LLC, Fresno, CA) is a portable system consisting of 5 integrated sensors and a processing/storage unit. The processing unit clips at the waist and the sensors are taped to the skin on the soles of both feet, on both thighs, and one sensor on the chest. The sensors measure angles of body segments and accelerations in two orthogonal directions. The monitor collects movement data continuously at 32 samples per second and integrates the information to distinguish among different postures and gaits. Output measures from the software include EE (kcal/min), speed and distance, power output, and an activity code that specifies the body position and activity being performed.

A recent report (15) demonstrated that the IDEEA can accurately detect the type, onset, duration, and intensity of most fundamental movements with 98% accuracy. Correlations between estimated and actual speed of movement were almost perfect ($r = 0.986$). A follow-up report (16) evaluated the accuracy of the EE estimates from the internal IDEEA algorithms. The EE estimations from the IDEEA monitor were 99% accurate compared with a mask calorimeter and 95% accurate compared with estimates from a metabolic chamber. There was little or no effect from body weight, height, BMI, or age on the accuracy of the estimations. While the IDEEA cannot be considered a true criterion measure, it provides a useful comparison measure for this field based study.

SP2 Monitor

The SP2 monitor (BodyMedia, Pittsburgh, PA) is a wireless body monitor that is worn over the triceps of the right arm. The SP2 uses a series of non-invasive biometric sensors to continuously measure different physical parameters (heat flux, galvanic skin response, skin temperature, near-body temperature, and motion, determined from a 2-axis accelerometer). Proprietary algorithms that take into account gender, age, height, and weight are then used to estimate EE (13). The first-generation algorithms were found to underestimate most locomotor movements but overestimate arm ergometer activity (13). Estimates were found to be much improved when the algorithms were refined based on the additional data collected in this first published report. This version of the software (Interview Research Software, version 3.9) has been shown to have improved utility in recent studies (12,14), but additional enhancements have been made in the software (Interview Research Software, version 4.0/4.1) to further improve the pattern recognition algorithms. To date, studies based on these algorithms have not been reported in the scientific literature. The present study will compare the results from the version 3.9 software (SP2v1) with results from the current 4.0/4.1 version of the software (SP2v2).

MTI Actigraph

The MTI (MTI Health Services, Fort Walton Beach, FL) is the most widely used and accepted accelerometer for field-based PA monitoring. The MTI is worn on a belt or belt clip at the midaxillary line of the right hip. The MTI uses a built-in single axis accelerometer designed to detect normal human motion. The monitor outputs activity counts, which reflect the summation of accelerations recorded during a given cycle period. An extensive body of research has supported the validity of the MTI as an objective indicator of PA (1,11). Despite the widespread usage, there is still considerable confusion due to the availability of multiple equations and cut-off points for reducing these data.

Data Collection

Participants reported to the laboratory between 7:00 and 9:00 AM on the morning of their scheduled day of testing. Height and weight were determined with standard physician scales. Body composition (% body fat) was estimated using a "foot to foot" bioelectric impedance analyzer (Tanita, Inc., Arlington Heights, IL). Participants were asked to self-assess their level of physical activity using a simple 9-point scale, with 1 being completely sedentary and 9 being very active. This measure was required for initialization of the IDEEA monitor.

The MTI and SP2 were set to record at 1-minute intervals and initialized according to manufacturer's recommendations using the same computer. The IDEEA monitor records data on a second-by-second basis, so initialization was conducted at the start of a minute to allow synchronization with the other monitors. The participants were fitted with the three monitors and asked to wear them for the rest of the day during all of their normal activities. Participants were asked to refrain from swimming and showering during the day and were asked to keep an activity log to help interpret possible irregularities in the data and/or adjust for non-wearing times. After wearing the monitors for the remaining portion of the day, participants reported back to the laboratory and had them removed. The IDEEA, SP2, and MTI monitors were downloaded and processed to facilitate temporal matching of the data. Raw data were exported in 1-min intervals and saved in separate files for each subject and monitor. The individual data files were then merged by ID number and a synchronized time variable to create the final dataset.

Data Processing

Additional processing of the data was conducted to compute the outcome measures of EE (kcal/kg per day) and PA (min/d) for each monitor. This processing is summarized below:

IDEEA Monitor

The IDEEA monitor yields an outcome measure of EE in kcal/min. These values were converted into METS (kcal/kg per day) to allow the estimates to be independent of body size. These conversions used an assumed resting metabolic rate of 1 kcal/kg per hour or 0.0167 kcal/kg per minute. Estimates of time spent in PA were determined with the IDEEA monitor by computing the number of minutes with MET levels above 3.0. This level is generally considered to be the threshold to define moderate-to-vigorous PA (MVPA).

SP2 Monitor

Two comparison measures of METS were created from the SP2 monitor using the same extrapolation procedures as those used for the IDEEA. The EE estimate from the original SP2 software (version 3.9) was used to yield one estimate (SP2v1). The second estimate was derived using a new set of pattern recognition algorithms that have recently been developed and released (version 4.1) by the manufacturer (SP2v2). These algorithms were not available with the software at the time of the study, so estimates based on the algorithms were obtained directly from the manufacturer. The raw SP2 data files were sent to the manufacturer (without any other data), and the resulting EE estimate was then processed to yield this alternate estimate of EE.

The SP2 monitor provides a direct estimate of PA based on the movement patterns detected by the pattern recognition software (SP2_SW). Two additional estimates of PA were computed by calculating the number of minutes above the 3.0 MET threshold value for both the original SP2 algorithm (SP2v1) and the new version (SP2v2).

MTI Actigraph

Six different estimates of EE (METS) were computed with the MTI monitor. The MTI software includes three different estimates that are available within the software. One is based on a standard "work-energy theorem" (MTI_WET), the second employs the published Freedson equation (17): EE (kcal/min) = (0.00094 cts/min) + (0.1346 Wt) − 7.37418 (MTI_F), and a third uses the work energy theorem for low intensity activity and the Freedson equation for activity counts over a threshold of 1952 counts/min (MTI_C). Two equations from Hendleman (7) were also examined. One equation is based on lifestyle activities: EE (METS) = 0.000638 cts/min + 1.602 (MTI_H), while the other one is based on walking: EE (METS) = 0.000409 counts/min +2.922 (HTI_Hw). The lifestyle-based equation developed by Schwartz et al. (8): EE (METS) = (0.0006863 counts/min) + 2.606 was used as the final MTI outcome measure (MTI_S).

Five different estimates of PA were compared with the MTI monitor: The Freedson cut-off point of 1952 (MTI_F), the Hendleman lifestyle-based cut-off point of 190.7 (MTI_H), the Hendleman walking equation cut-off point of 2191 (MTI_Hw), the Schwartz cut-off point of 576, and a new cut-off point value proposed by Matthews (11) of 760 counts/min (MTI_M). This last cut-off point value was based on an empirical analysis of raw data from other calibration studies on the MTI monitor. Activity estimates from the associated MTI_WET and the MTI_C are not relevant since they are used for estimating EE below the designated activity threshold.

Statistical Analyses

The statistical analyses compared the estimates of EE and PA from the IDEEA monitor with comparable outcome

Table 1. Characteristics of sample population

	N	Age (yr)	Height (m)	Weight (kg)	BMI (kg/m^2)	Body fat (%)	Self-reported fitness rating (1 to 10)
Male	13	25.2 ± 5.4	1.80 ± 0.07	88.1 ± 24.0	27.2 ± 7.0	18.7 ± 7.9	6.5 ± 1.7
Female	17	24.6 ± 6.7	1.66 ± 0.06	68.6 ± 13.0	24.9 ± 4.3	30.0 ± 8.5	6.0 ± 1.7
All	30	24.9 ± 6.1	1.72 ± 0.10	77.1 ± 20.7	25.9 ± 5.6	25.1 ± 9.9	6.2 ± 1.7

measures from various SP2 and MTI equations/algorithms. Differences in estimates of EE and time (minutes) spent in MVPA were evaluated with univariate t tests. Pairwise correlations among the different EE and PA measures were used to evaluate the overall level of agreement between the methods. Correlations were computed separately for each individual (using the minute-by-minute data), and the mean correlation was used to reflect the overall level of agreement. Correlations were also computed separately for each major activity type coded on the IDEEA to examine possible differences in agreement for different activities. Bland Altman plots (18) were used to examine the individual agreement across the range of PA levels. In these plots, the difference between estimates (criterion-comparison) was plotted on the y-axis while the mean of the estimates ((criterion +comparison)/2) was plotted on the x-axis. Confidence intervals defining the limits of agreement were established as ± 2 standard deviations from the mean difference. Statistical analyses were conducted using SAS, version 9.0.

Results

The descriptive statistics for the sample are provided in Table 1. The participants ranged in age from 19 to 46 years. The BMI values ranged from 20.3 to 40.1 kg/m^2 for males and from 18.6 to 33.4 kg/m^2 for females. Body fat percentages ranged from 6.5% to 33.4% for males and from 15.8% to 45.2% for females. The self-reported activity levels (required for the programming of the IDEEA monitor) ranged from 3 to 9 for both males and females, indicating that there was reasonable diversity in the sample in activity levels.

Each participant in the study wore the MTI, SP2, and IDEEA monitors during their normal daily activities. The average monitoring period for participants was 346 ± 49 minutes. Participants were typically involved in campus-related activities (e.g., classes, walking around campus) during the day. Few participants reported engaging in structured bouts of vigorous activity during the day, so emphasis was placed on the detection only of MVPA.

Energy Expenditure Estimates

The descriptive statistics for the EE estimates are provided in Table 2. The differences in EE estimates between the IDEEA and MTI ranged from −1.10 METS to 0.46 METS. The estimates from the Schwartz and Hendleman lifestyle equations significantly overestimated EE (0.93 METS and 1.1 METS, respectively, $p < 0.05$), while the MTI_WET significantly underestimated EE (0.43 METS, $p < 0.05$). The Freedson equation tended to underestimate EE levels (mean difference = 0.38 METS), but this was not a statistically significant difference. The closest estimations were from the Hendleman walking equation (difference = 0.10 METS) and the two estimates from the SP2 armband. The original (version 3.9) SP2 algorithms (v1) yielded values that were within 0.12 METS, while the revised (version 4.1) SP2 algorithms (v2) yielded overall EE estimates that were within 0.01 METS (not significant).

A unique advantage of the IDEEA monitor is that it provides a listing of different activity types registered during the data recording. A total of 39 different activities were found in the 10,364 minutes of combined IDEEA data. Because many of the activity codes are derivatives of the same basic postures or movements, the data were collapsed into seven predominant postures/movement patterns (lie, lie variations, sit, sit variations, stand, stand variations, and walking) to facilitate interpretations. Mean EE estimates for each activity category are provided in Table 2. There was not a large enough sample of stepping, running, or jumping to obtain stable statistics, so these were omitted from the table. The variations captured with the additional activity codes reflect subtle distinctions or differences from the predominant activity categories (e.g., leaning is a variation of standing) and should be viewed as analogous or similar to the main activity.

The errors in the EE estimates were highly variable for the different devices/equations that were studied. The Hendleman equations and Schwartz equations were found to overestimate almost all activities; the exception was the non-significant difference observed for the walking activity with the Hendleman equation. Interestingly, the Hendleman

Table 2. METS from the different monitors and equations processed by primary activity categories recorded on the IDEEA

		IDEEA [mean (SD)]	SP2v1 [mean (SD)]	SP2v2 [mean (SD)]	MTI [mean (SD)]	MTI_F [mean (SD)]	MTI_H [mean (SD)]	MTI_Hw [mean (SD)]	MTI_S [mean (SD)]
All activities	Mins (%)	2.04 (0.42)	1.92 (0.49)*	2.05 (0.56)	1.61 (0.29)*	2.43 (0.12)	3.14 (0.10)*	1.94 (0.16)	2.97 (0.17)*
Lie	1100 (10.6%)	1.25 (0.18)	1.22 (0.32)	1.29 (0.30)	1.05 (0.05)*	2.03 (1.39)*	2.94 (0.02)*	1.63 (0.03)*	2.64 (0.03)*
Lie variations	181 (1.8%)	1.43 (0.60)	1.60 (0.88)	1.55 (0.52)	1.15 (0.14)*	2.39 (1.65)	2.97 (0.05)*	1.68 (0.08)*	2.69 (0.09)*
Sit	1911 (18.4%)	1.48 (0.17)	1.39 (0.32)	1.47 (0.30)	1.11 (0.08)*	2.09 (1.36)*	2.96 (0.03)*	1.67 (0.04)*	2.67 (0.05)*
Sit variations	3288 (31.7%)	1.55 (0.20)	1.31 (0.27)*	1.38 (0.25)*	1.08 (0.06)*	2.06 (1.36)	2.95 (0.02)*	1.65 (0.03)*	2.65 (0.03)*
Stand	1537 (14.8%)	2.08 (0.28)	2.48 (0.59)	2.38 (0.57)	1.40 (0.12)	2.28 (1.32)	3.06 (0.04)	1.83 (0.69)	2.85 (0.07)
Stand variations	938 (9.0%)	2.30 (0.43)	2.69 (0.84)	2.60 (0.84)	1.55 (0.37)	2.38 (1.33)	3.12 (0.13)	1.91 (0.21)	2.94 (0.22)
Walk	1286 (12.4%)	4.15 (0.45)	3.58 (0.61)	4.26 (0.89)	4.24 (0.79)	4.23 (0.85)	4.08 (0.28)	3.40 (0.44)	4.54 (0.47)

METS, mean energy expenditure estimates; EE, energy expenditure; IDEEA, IDEEA EE estimate; SD, standard deviation; SP2v1, main EE equation for SP2 band; SP2v2, new EE equation for SP2 band; MTI, main equation for MTI; MTI_F, Freedson equation for MTI; MTI_H, Hendleman EE equation; MTI_Hw, Hendleman walking equation; MTI_S, Schwartz EE equation. Values represent the mean and SD of the mean METS (kcal/kg per hour) for each individual. Percentages for minutes do not sum to 100% because aggregate codes with frequencies less than 1% were excluded.

* Significantly different than value from IDEEA monitor ($p < 0.05$).

walking equation was found to significantly overestimate the four sedentary positions (lie/sit) but to significantly underestimate the three more active positions, including the walking position. This suggests that the non-significant difference observed with this device across the whole day was due to the canceling of errors from sedentary and active periods. This type of determination would not be possible without the segmentation by activity type allowed by the IDEEA monitor.

The Freedson equation tended to overestimate the sedentary position but yielded non-significant differences for the standing and walking positions. The MTI_WET yielded closer estimates for the sedentary positions, but they were all significantly lower than the estimates from the IDEEA monitor. The combined use of the work energy theorem and the Freedson equation within the MTI software appears to have some merit, but the results here suggest that estimates would be better if the Freedson equation was used over a wider range than is currently used. The Freedson equation is used only for counts exceeding the MVPA cut-off point of 1952, but the equation appears to be accurate for activities classified as "light" as well.

The estimates from the SP2 armband were found to be accurate for lie, lie variations, and sit, but there was a tendency for overestimation of EE for the remaining positions (sit variations, stand, stand variations, and walking). The new (version 4.1) SP2 algorithms provided more accurate estimates than the previous algorithms for all seven of the activities, as the errors tended to be smaller with the SP2v2 estimate than with the SP2v1. It is important to note that the new SP2v2 equation yielded non-significant differences for the walking activities.

Pairwise correlations with the IDEEA monitor were computed using the minute-by-minute outputs to examine the overall agreement among the measures. Separate correlations were computed for each individual, and the mean correlation was used to reflect the overall agreement among the devices for this outcome measure. Overall, the correlations among all measures were quite high. The mean correlation with the IDEEA monitor ranged from $r = 0.71$ to $r = 0.88$ for the different devices (Table 3). The relationships were quite consistent across the participants, with the standard deviation for the mean correlations ranging from 0.06 to 0.08.

Correlations were also computed for each of the different activity types to examine the overall agreement across individuals (Table 4). The correlations were uniformly high for the MTI equations across all of the activity types. In contrast, the correlations with the armband equations tended to be a bit lower for some of the activities. It should be noted that the comparisons for activity type are based on the activity type observed at the end of a given minute. If activity patterns varied considerably within a minute or changed right at the end of the minute, some of the codes

Table 3. Individual correlations of energy expenditure estimates from the two SP2 equations and a representative estimate from the MTI Actigraph

ID	Minutes	IDEEA-SP2v1	IDEEA-SP2v2	IDEEA-MTI_F
1	283	0.72	0.80	0.86
2	343	0.77	0.88	0.96
3	433	0.59	0.82	0.89
6	307	0.75	0.87	0.92
7	319	0.73	0.80	0.94
8	371	0.63	0.68	0.69
9	338	0.91	0.70	0.77
10	481	0.70	0.78	0.86
11	341	0.72	0.79	0.77
12	309	0.69	0.80	0.78
13	321	0.78	0.79	0.91
14	392	0.62	0.74	0.79
15	403	0.64	0.85	0.88
16	311	0.80	0.90	0.94
17	289	0.69	0.85	0.91
18	362	0.69	0.84	0.83
19	421	0.63	0.77	0.95
20	373	0.68	0.86	0.93
21	401	0.74	0.78	0.94
23	355	0.83	0.92	0.96
24	301	0.59	0.71	0.94
25	330	0.70	0.85	0.90
27	306	0.75	0.87	0.93
29	320	0.77	0.79	0.75
30	266	0.73	0.86	0.90
31	401	0.81	0.90	0.96
32	316	0.68	0.85	0.93
33	352	0.69	0.86	0.91
34	311	0.65	0.74	0.93
35	308	0.65	0.85	0.87
Mean (standard deviation)	345 (49.8)	0.71 (0.07)	0.82 (0.06)	0.88 (0.07)

SP2, Sensewear Pro II; IDEEA, Intelligent Device for Estimating Energy Expenditure and Activity; EE, energy expenditure; SP2v1, main EE equation for SP2 band; SP2v2, new EE equation for SP2 band; MTI_F, Freedson equation for MTI Actigraph.

may be misrepresented. Because of the large number of minutes in the day and the broad categories that were used in processing (e.g., lying, sitting, standing, walking), it is not likely that the observed patterns would be altered in a significant way.

Physical Activity Estimates

Comparisons were also made in the estimates of PA obtained from the different devices (Table 5). The absolute estimates of time spent in PA were highly variable (34.3 to 107.1 minutes). The lowest mean activity estimates were reported with the Hendleman (MTI-HW) walking equation and the Freedson equation (34.3 and 38.3 minutes, respectively). The highest estimate was found with the Hendleman (MTI-H) lifestyle equation (107.1 minutes). All differences (IDEEA value − estimate value) were statistically significant, but the error was least for the SP2v2 equation and the Matthews MTI cut-off point. Bland Altman plots were used

Table 4. Correlations of IDEEA energy expenditure estimates with various SP2 and MTI algorithms by activity type

Activity code	Activity	Minutes (%)	Sensewear Pro II		MTI				
			SP2v1	SP2v2	MTI_WET	MTI_F	MTI_H	MTI_HW	MTI_S
1	Lie	1100 (10.61%)	0.62	0.66	0.80	0.62	0.63	0.70	0.67
2	Lie variations	181 (1.75%)	0.89	0.94	0.85	0.76	0.78	0.83	0.81
3	Sit	1911 (18.44%)	0.42	0.51	0.85	0.84	0.85	0.88	0.87
4	Sit variations	3288 (31.73%)	0.48	0.53	0.77	0.78	0.79	0.82	0.81
5	Stand	1537 (14.83%)	0.59	0.63	0.79	0.71	0.74	0.81	0.79
6	Stand variations	938 (9.04%)	0.53	0.60	0.71	0.75	0.78	0.82	0.82
7	Walking	1286 (12.41%)	0.61	0.63	0.79	0.83	0.85	0.84	0.85

EE, energy expenditure; IDEEA, IDEEA EE estimate; SP2, Sensewear Pro original; SP2v1, Sensewear Pro modified; MTI_WET, MTI Work Energy Theorum; MTI_F, Freedson; MTI_H, Hendleman lifestyle; MTI_HW, Hendleman walking; MTI_S, Schwartz. Percentages for minutes do not sum to 100% because aggregate codes with frequencies less than 1% were excluded.

to examine the distribution of error for estimation of time spent in PA (Figure 1). The patterns did not exhibit any systematic form of bias, but the relationships were tighter for the Matthews and the SP2 estimates (Figure 1).

Correlations with the IDEEA monitor were consistently high for all of the devices/equations (range: $r = 0.77$ to $r = 0.94$). Pairwise correlations among the different devices/equations were generally moderate to high. The Hendleman walking equation and the Freedson equation, however, were only moderately correlated with the SP2 estimates (range: $r = 0.61$ to $r = 0.66$). Most other correlations exceeded 0.76.

Discussion

This study examined the accuracy of estimated EE and PA duration from the MTI Actigraph monitor and the SP2 armband monitor under free-living conditions. Reconciling differences between outcome measures from different de-

Table 5. Descriptive statistics for physical activity (minutes per day) for each device and correlations of physical activity estimates among the different devices

	Mean (min)	Standard deviation	SP2	SP2v1	SP2v2	MTI_WET	MTI_F	MTI_H	MTI_Hw	MTI_S	MTI_M
IDEEA	52.0	31.8	0.77	0.84	0.90	0.94	0.91	0.79	0.89	0.90	0.94
Sp2 (PA estimate)	94.8	47.0	—	0.92	0.90	0.84	0.65	0.93	0.61	0.90	0.85
SP2v1 (equation1)	82.5	44.2		—	0.95	0.81	0.66	0.84	0.64	0.85	0.82
SP2v2 (equation2)	66.9	36.9			—	0.89	0.78	0.84	0.75	0.91	0.90
MTI_WET	59.3	29.9				—	0.91	0.87	0.87	0.98	0.99
MTI_F (Freedson)	38.3	26.2					—	0.69	0.99	0.81	0.89
MTI_H (Hendleman)	107.1	42.9						—	0.64	0.93	0.88
MTI_Hw (Hendleman)	34.3	25.0							—	0.76	0.84
MTI_S (Schwartz)	71.7	33.0								—	0.98
MTI_M (Matthews)	62.9	30.7									—

SP2, Sensewear Pro original; SP2v1, Sensewear Pro modified; MTI_WET, MTI Work Energy Theorum; MTI_F, Freedson; MTI_H, Hendleman lifestyle; MTI_HW, Hendleman walking; MTI_S, Schwartz. The Main MTI equation was not listed here since it utilizes the Freedson equation for all count values >1952.

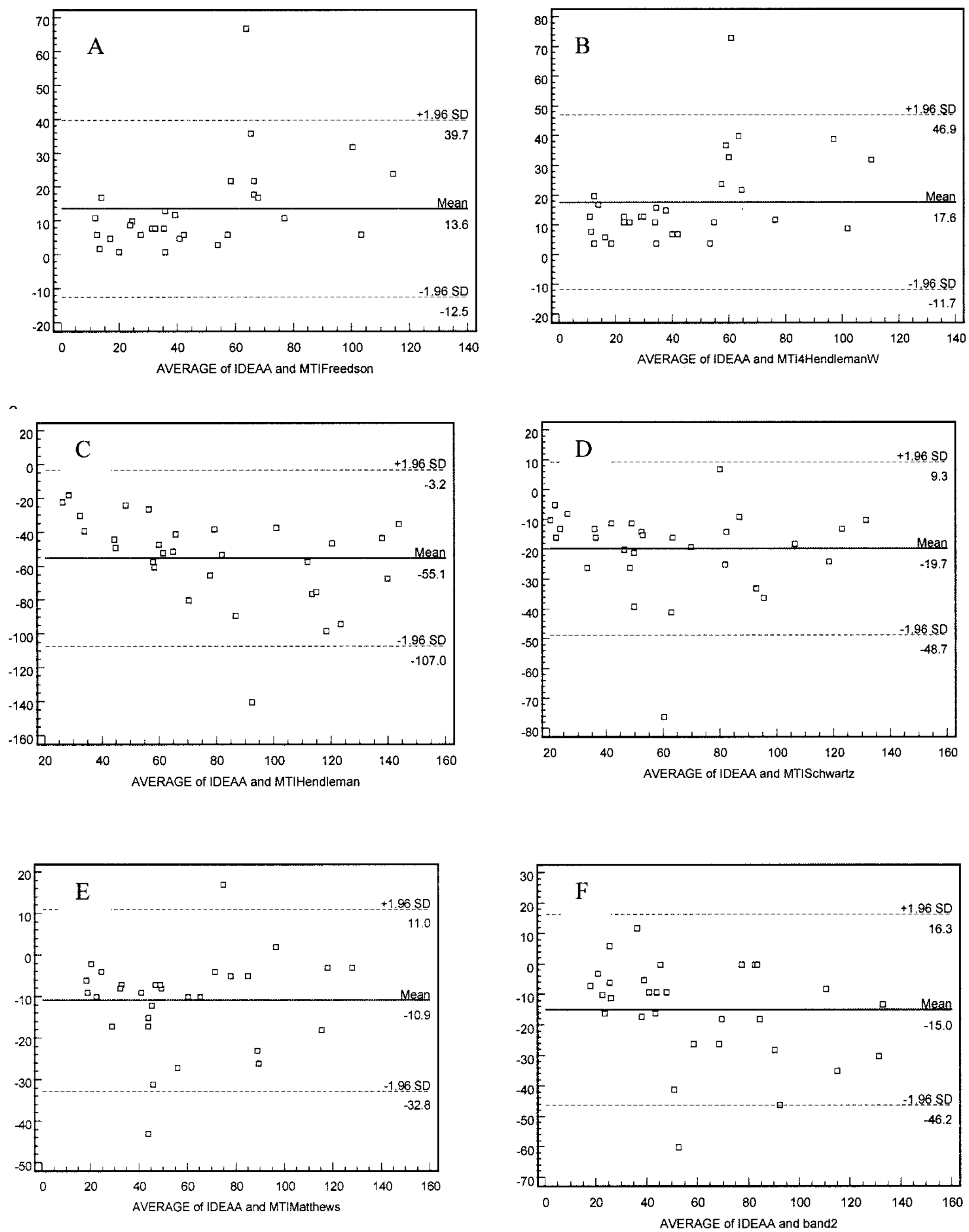

Figure 1: Bland Altman plots for estimates of moderate-to-vigorous physical activity.

vices (or different values from a given device) has proven difficult in other studies due to the lack of an appropriate criterion measure. The IDEEA monitor accurately detects free-living gait and postures (15) and accurately estimates free-living EE (16). While it cannot be viewed as a perfect criterion measure, it provided an effective comparison measure for this field-based study.

As expected, the PA and EE estimates from the MTI were highly variable and dependent on the type of equation that was used. Our results confirm those of Strath et al. (10) and Schmidt et al. (9), as we found the Hendleman lifestyle equation to grossly overestimate EE and levels of PA. The results with the other equations were more variable, but some generalizations of the patterns are described. In general, equations based on "lifestyle" activities (e.g., Hendleman and Schwartz equations) tend to have higher intercepts and flatter slopes compared with equations developed using locomotor movements (11). These lifestyle equations tended to overestimate EE and PA for the free-living activities evaluated in the present study: the higher intercepts in these equations lead to overestimation of the energy costs from low intensity activities. In contrast, equations based purely on locomotor activities (e.g., Freedson, Hendleman walking) tended to underestimate total daily EE or PA. This is because these equations or cut-off points are based on activities that have a relatively high movement-to-EE ratio. Lifestyle activities involving a lot of upper body movements tend to have higher energy costs for the amount of movement detected, and this increased energy cost would not be captured by these equations.

The EE and PA estimates from the IDEEA monitor (viewed as criterion estimates) tended to fall between the values computed with the lifestyle and locomotor-based equations. This suggests that both approaches may have limitations for evaluating normal free-living activity. The relative accuracy of lifestyle and locomotor equations would likely depend on the contribution of lifestyle activity equations to an individual's total daily activity pattern. The generally strong results for the combined MTI algorithms that are used internally in the software are consistent with this observation. This algorithm uses the MTI_WET for rest activities and the Freedson equation at higher intensity levels. In support of this approach, we noted that the estimations with the MTI_WET were more accurate for the lower intensity activities while the results with the Freedson equation were more accurate for the standing and walking activities. The average bias across the seven activities (mean = 0.40 METS) was lower for the combined approach than for either the WET or the Freedson equation used alone (data not shown).

With regard to PA estimates with the MTI, we found the least error and highest correlation for the cut-off point value recently proposed by Matthews (11). This cut-off point of 760 counts/min was derived using calibration data from a number of different sample populations, including both locomotor and lifestyle-based activities. The combination approach used to develop this new cut-off point may have allowed it to find the optimal balance between lifestyle and treadmill approaches. Crouter et al. (19) recently described a two-equation methodology for estimating EE and PA with the MTI monitor. In this approach, minutes are categorized as either locomotor or non-locomotor minutes; separate equations are then used to estimate the energy cost of the activity. This approach is an advance over previous methods because it allows for separate equations to be used. The methodology is currently being considered for inclusion in the MTI software program, but it was not available for use in the present study. Based on the convincing findings in the published report (19), it is likely that the two-equation approach would have yielded the most accurate estimates for the MTI.

The SP2 armband provided an interesting comparison measure in the present study because it uses a pattern recognition approach for activity and EE estimation that is conceptually similar to the approach used by the IDEEA monitor. An advantage of the pattern recognition approach is that separate EE algorithms can be used depending on the type of activity that is detected. Traditional accelerometers such as the MTI quantify the total movement that is performed and then rely on a single calibration equation to process or reduce the accelerometer data. As described previously, there are unique movement-EE relationships for different activities, so it may be unreasonable to expect a single calibration equation to accurately capture total daily EE. The use of different prediction equations based on the type of movement that is detected may allow for reduced error in EE and PA estimations. The Crouter et al. methodology (19) described above has the same basic advantage, but the method is based on detecting differences in activity patterns rather than actually discriminating between the fundamental movements or patterns in a specific activity. Specifically, the Crouter et al. method (19) uses differences in the coefficient of variation in sequential minutes to distinguish locomotor and non-locomotor movements. This improves the accuracy of the MTI estimations, but the limited number of channels and memory in the MTI limits the ability to expand on this methodology.

The results in this study provide some support for the utility of the pattern recognition approach used in the SP2. Correlations with the IDEEA monitor were similar with the MTI and the SP2 equations, but the overall estimates of EE and PA were generally more consistent with the SP2. The results with the original (version 3.9) SP2 algorithms (SP2v1) were within 0.12 METS for the mean EE estimate over the whole monitoring period. The mean bias across the seven activities was also lower (0.27 METS) than comparable values for the MTI equations (Table 2). This indicates reduced error for estimation of specific activities. The tighter overall relationships are likely due to the ability of the armband to discriminate between the rest and the active periods and to use appropriate predication equations depending on the type of movement that was detected.

Several other recent studies have reported promising results with the SP2 armband monitor. King et al. (14) reported that the SP2 provided accurate estimate of EE during locomotor activity across a wide range of speeds. Fruin and Rankin (12) demonstrated good agreement between the SP2 and measured EE values from a metabolic cart for both rest and cycle ergometry. While the original SP2 algorithm yielded reasonable results in our study, we found that the revised algorithms included in the version 4.1 firmware upgrade (SP2v2) produced more accurate estimates of EE and PA. The mean MET values from these algorithms were within 0.01 METS of the overall daily estimate from the IDEEA monitor, and the mean bias in EE across the seven different activities was only 0.15 METS. These results support the utility of the revised algorithms available with the firmware upgrade to version 4.1 software.

A technological challenge with pattern recognition devises is to "train" the sensors to accurately detect different movement patterns. The IDEEA monitor uses five different sensors and a complex neural network to detect different postures and movement patterns. The increased sophistication of the IDEEA monitor may allow it to provide a more accurate indicator of EE, but the need for multiple sensors and wires may make it too cumbersome for monitoring over a number of days. The results from the SP2 device indicate that reasonably accurate estimations of EE and PA can be obtained in the field with a less invasive armband device. A potential advantage of the SP2 is that it incorporates physiological measures such as galvanic skin response, heat flux, and skin temperature. These sensors are used to help discriminate between activity and inactivity. While not included in the present study, the SP2 also includes estimates of sleep time. The details of the algorithm development are proprietary, but presumably the software detects sleep by integrating the motion sensing data with changes in the galvanic skin response. The IDEEA approach is based primarily on motion and does not provide estimates of sleep.

In summary, we found that the estimates from the MTI and SP2 were all highly correlated with estimates from the IDEEA monitor (and with each other), but there were marked differences in estimates of EE and activity level from the different measures. Overall, the best agreement in terms of absolute estimates of EE and levels of PA was found with the new SP2 armband algorithms included in the version 4.1 firmware upgrade. Definitive conclusions regarding the most appropriate MTI equation and cut-off point are not possible because the results are likely to depend on the sample population and the type and intensity of activities that are performed. There is sufficient evidence, however, to discontinue use of the Hendleman lifestyle (MTI_H) equation. Three different studies, the present study as well as those by Schmidt et al. (9) and Strath et al. (10), have all reported similar overestimation of EE and PA based on this equation. The results in this study indicated that the combined EE estimation within the MTI software provides the most accurate estimate of overall EE, and the new Matthews cut-off point (11) provides the most accurate estimate of PA. The new Crouter et al. methodology (19) also offers promise for improving estimates with the MTI monitor.

A limitation of the present study is that it was not possible to examine the higher range of PA intensity. Only one or two participants reported engaging in any vigorous activity during the daily monitoring, so additional research is needed to determine if the results would be consistent with more vigorous bouts of activity performed during the day. Another limitation is that the present data were collected on college students, who have unique lifestyle patterns. Different results may be obtained with different sample populations, so additional cross validation may be needed. A final limitation is that it was not possible to determine precise transition points for changes in the specific activity codes. The data from the monitors were aggregated at the minute-by-minute level, and there may be some variability within individual minutes of data. This could lead to slight alterations in the values presented for specific types of activities but would not likely influence the overall patterns or relationships that were presented.

Refinements in the processing and interpretation of data from the IDEEA and SP2 will help to advance measurement research on physical activity. Both instruments seem well suited to serve as criterion measures of field-based activity due to their ability to detect different patterns of physical activity. Comparisons with portable indirect calorimetry units and doubly labeled water are needed to further establish the accuracy of these new monitoring technologies.

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