Measurement of Human Daily Physical Activity

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Abstract

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Objectives: To validate a new device, Intelligent Device for Energy Expenditure and Activity (IDEEA), for the measurement of duration, frequency, and intensity of various types of human physical activity (PA).

Research Methods and Procedures: The ability of IDEEA to identify and quantify 32 types of PA, including the most common daily exercise and nonexercise PA, was tested in 76 subjects: Subjects included males ($N = 33$) and females ($N = 43$) ranging in age from 13 to 72 years with a mean body mass index (BMI) of 24.7 kg/m^2 (range: 18.4 to 41.0) [43 females: 13 to 72 years old and BMI 18.4 to ~41.0 kg/m^2 (mean = 24.7 kg/m^2**);** 33 males: 15 to ~72 years old and BMI 21.0 to ~38.4 kg/m^2 (mean = 25.9 kg/m^2)]. Postures, limb movements, and jumping were tested using a timed protocol of specific activities. Walking and running were tested using a 60-meter track, on which subjects walked and ran at 6 self-selected speeds. Stair climbing and descending were tested by timing subjects who climbed and descended a flight of stairs at two different speeds.

Results: Correct identification rates averaged 98.9% for posture and limb movement type and 98.5% for gait type. Pooled correlation between predicted and actual speeds of walking and running was high ($r = 0.986$, $p \leq 0.0001$).

Discussion: IDEEA accurately measured duration, frequency, type, and intensity of a variety of daily PAs.

Key words: physical activity, exercise, posture, nonexercise activity, gait

Introduction

Regular physical activity (PA),[1] fitness, and exercise are critically important for the health and well being of people of all ages (1). However, measuring PA levels is a formidable task. As Montoye et al. pointed out: "While most experts agree that remaining active throughout life is important for continued health and fitness, measuring activity levels outside of the laboratory is difficult" (2). Measurement techniques have evolved considerably over the years (3,4), creating a shifting pattern of strength and weakness in the evidence supporting the assertion that PA improves health (3,5). The complexity is heightened by the different health implications of measuring activity, gauging intensity, and assessing fitness (3). Particularly challenging have been the attempts to develop accurate, valid, and cost-effective techniques to quantify PA under free living conditions (6,7,8). Numerous methods have been used to measure short- and long-term PAs. They vary greatly in their applicability (6,9,10). A pedometer is a small, simple, and noninvasive mechanical movement counter that is clipped to a belt at the waist or worn on the ankle (11,12). The main shortcoming of pedometers is that they are not sensitive to gait differences such as stride length, which vary significantly among activities from person to person. Accelerometers are currently used by several groups for PA monitoring. Level walking showed the highest correlation with the waist-worn tri-axial accelerometers after individual calibration ($r = 0.99$) (13). This indicates the excellent reproducibility of the device in monitoring human movement as long as the type of activity is known for that person. The advantages of this class of devices include small size, noninvasiveness, low cost, and minimal intrusion to normal subject movements during daily activities. The duration, frequency, and, to some extent, intensity are also measurable. The major problem is that the device detects only the moving or shaking of the sensor that is attached to part of the body. It is not "smart" enough to know what type of PA is being performed. The single sensor location makes it

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[1] Nonstandard abbreviations: PA, physical activity; IDEEA, Intelligent Device for Energy Expenditure and Activity; EE, energy expenditure; BMI, body mass index; mph, miles per hour.

extremely difficult, if not impossible, to detect movement coordination of the limbs or determine postures and gaits.

Similar devices such as wrist/ankle watches and actometers also exist. Because most of these devices use switches as sensors, their "on" or "off" categories of information can only give qualitative type of results with limited information on the intensities of PA. Electronic load transducers and foot-contact monitors have been reported, which could be inserted into the heels of shoes to monitor walking activity and loads held, lifted, or carried (14). However, because of the technical and practical limitations of these measuring techniques, these devices (i.e., in-shoe step counters, foot-contact time monitors) have not been used widely in epidemiological research, and little information is currently available on their accuracy in assessing habitual PA status.

Because of the complex nature of PA and problems inherent to its accurate measurement (7), none of the more than 30 presently reported methods are capable of accurately identifying type, duration, frequency, and intensity of daily PA. Recently, a new microcomputer-based portable PA measurement device, Intelligent Device for Energy Expenditure and Activity (IDEEA) (MiniSun, Fresno, CA), which was designed to accomplish the complex measurements listed above, has become available. We report results of extensive testing of IDEEA for assessment of a wide variety of PA by measuring duration, frequency, and intensity. Specifically, tests were conducted for the following: identification of postures, limb movements, gaits, and speed estimation of walking and running.

Research Methods and Procedures

PA Classification

Functionally, human PA, such as writing a letter or watching television, can be very complicated. It can, however, be categorized into much simpler types when energy requirement is considered. Thus, based on our experience and the daily activities identified and suggested by other investigators (15–19), we included four general kinds of activity in our test: postures, gaits, limb movements, and transitions (Figure 1). The five primary postures—sitting, standing, reclining, leaning, and lying down—are relatively static. Each primary posture was further defined by a number of secondary postures, for a total of 22 secondary postures. There are five gaits that are dynamic: walking, running, climbing stairs, descending stairs, and jumping. The limb-movement category includes five activities involving movement of the feet and legs while sitting or standing. In total, we classified 32 types of PA from postures, gaits, and limb movements. A final category, transitions, includes periods of movements from one type of PA to another, which is very important for fidgeting studies.

All of the PAs shown in Figure 1 can be detected by the IDEEA system except for cycling and jumping on one foot. The activity classification in this study was focused on the daily activities that are performed by the majority of the population. These cover the most common daily PAs including both exercise and nonexercise.

Subjects

We recruited subjects through the hospital and neighborhood community by posting flyers and making phone calls. The subjects received a small monetary compensation for their participation. A total of 76 subjects (33 males and 43 females) were included in the study. Among these, 69 participated in the gait testing, whereas 68 participated in the posture testing. Mean values for the characteristics of all 76 subjects are shown in Table 1. All subjects appeared to be free of any impairment of the loco-motor system.

Device

A photo of the IDEEA is shown in Figure 2A. It consists of five small sensors (each $16 \times 14 \times 4$ mm, approximately the size of a small postage stamp) that are attached to the body and a small 200-gram data collection device (microcomputer) that can be worn on the belt. The output signals from the sensors travel through thin, flexible cables (OD = 2 mm) to the microcomputer. A fast microprocessor (33 MHz, 32-bit ARM processor; ARM, Cambridge, United Kingdom) is used for the intensive computational requirements. Analyses include identification of activity type, gait analysis during walking and running, and calculation of duration, frequency, and intensity of activity/exercise. A new memory technique called "flash memory" enables recording of the processed data and other vital information with high reliability during activities in free-living conditions. The recorded data will not be lost in the event of accidents, such as battery failure or inappropriate operations. If abnormal conditions should occur, a beeper would send various alarm signals through beeping frequencies and patterns to alert the wearer. The communication between the IDEEA and the main database such as a desktop computer is through a standard serial communication port (RS-232; 240,000 bytes per second) at high baud rate. This allows data to be downloaded in the laboratory by a home computer or through the Internet.

The basic working principle of an IDEEA is the following: the IDEEA system monitors body and limb motions constantly through five sensors attached to the chest, thighs, and feet. The different combinations of signals from those five sensors represent different PAs, which were coded as 32 different numbers for the 32 activities in this study.

These motion signals are first preprocessed by signal conditioners. The output electric signals representing motion and speed are then fed at high rate through a cable to the microcomputer data acquisition unit. The multi-channel raw data are temporarily stored in the random access memory. They are then further processed by the microprocessor

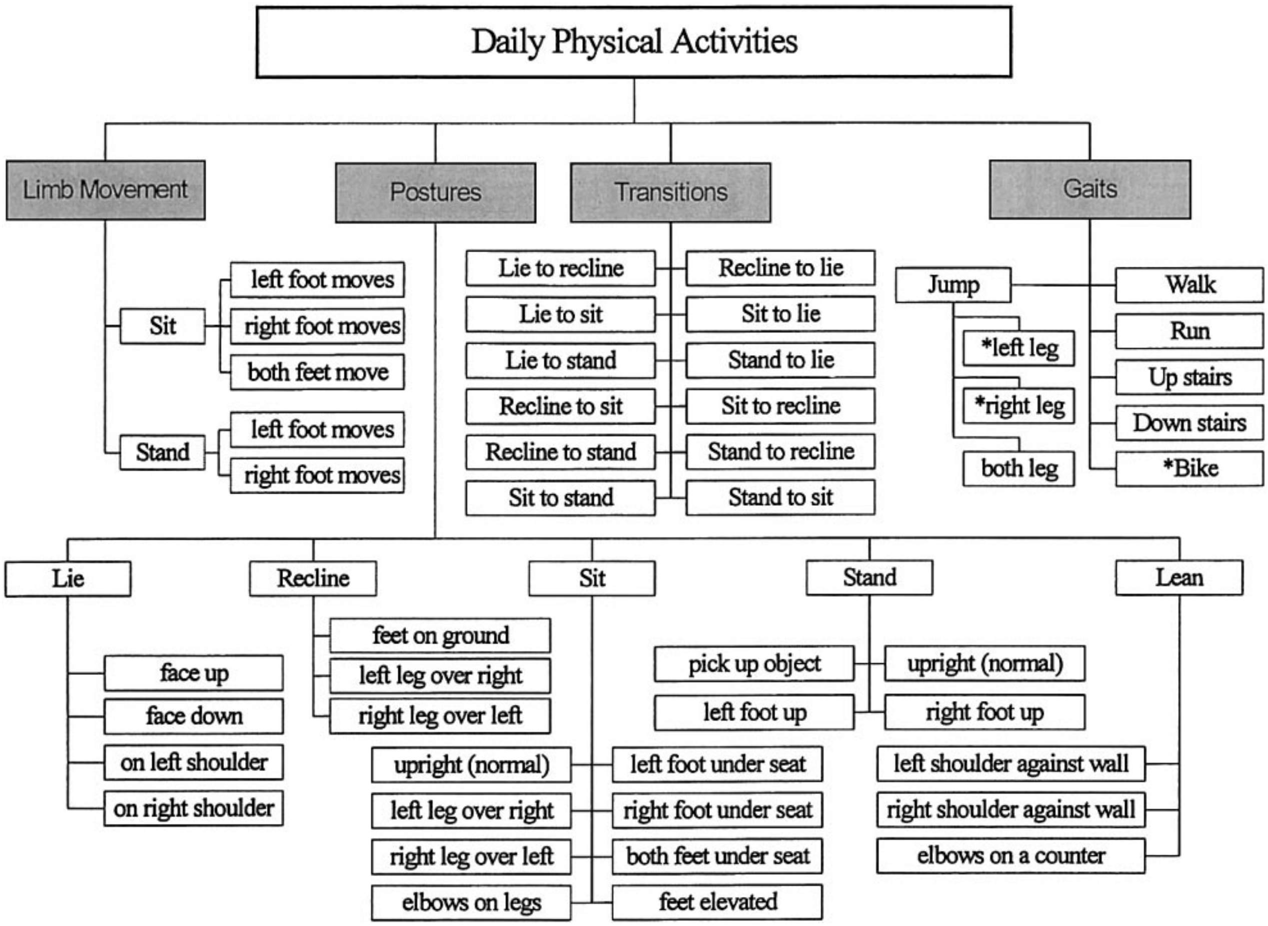


Figure 1: Classification of PA. Daily physical activities are characterized as five basic gaits (biking, jump on left, and jump on right foot were not evaluated in this study), five primary postures, and five limb movements and transitions. Each primary posture is further defined by a number of secondary postures, for a total of 22 secondary postures.

and stored in flash memory together with specific events and the subject's characteristics (age, gender, body weight, height, and estimated fitness level). These data are downloaded to a computer for analysis at the end of each test. IDEEA can operate for up to 48 hours and can store ~60,000,000 data units. Additional memory is needed if it is necessary to store all the raw data for a longer period.

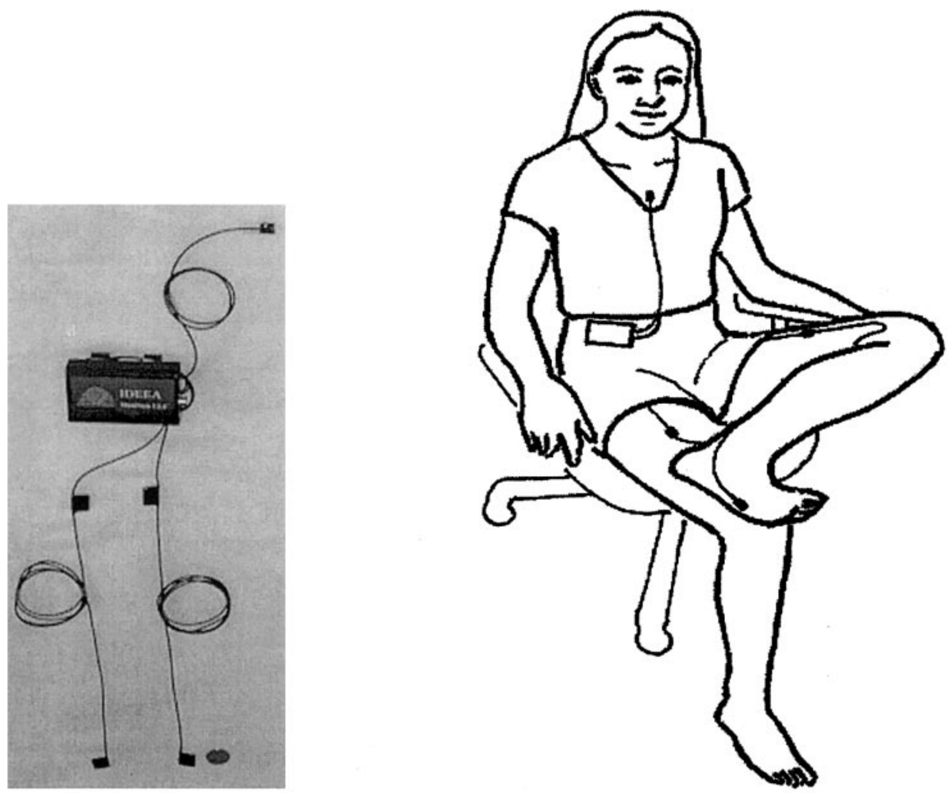
Table 1. Subject characteristics

	$N = 76$ ($n = 33$ males, $n = 43$ females)	
Characteristics	**Mean ± SD**	**Range**
Age (years)	36.3 ± 14.9	13.0 to 72.0
Body weight (kg)	72.4 ± 14.8	44.6 to 118.0
Height (cm)	170.9 ± 9.4	152.4 to 188.0
BMI (kg/m^2)	24.7 ± 4.4	18.4 to 41.0

The outputs of IDEEA provide the specific type (e.g., sitting, climbing stairs, jumping), duration, and estimated intensity, if applicable (such as the speed of walking and running) of daily activities on second-by-second basis (ranging from milliseconds to hours).

Device Placement and Speed Measurement Setup

For the tests, the five sensors were attached to the skin by hypoallergenic medical tape as described below. Although the exact location has not been proven to be critical, we placed sensors in the following locations: two sensors were placed at the anterior sides of the upper legs, halfway between the hip and knee; the two foot sensors were placed on the inferior side of the feet, under the arch to avoid interference with activities such as walking, running, and jumping; the fifth sensor was attached to the sternum, just below the sternal angle, vertical to the *x* axis. If necessary, a small wedge was inserted underneath the sensor to correct



A B

Figure 2: (A) The picture of the device and sensors; (B) the drawing that demonstrates the position of the sensors on a subject. A total of five sensors are placed: one on the chest, two on the frontal part of thighs, and two on the feet. Very thin and flexible wires (outer diameter, 2 mm) connect sensors and recorder.

for difference in anatomic inclinations, which are especially apparent for obese subjects. For the calibration of IDEEA, the subject was asked to sit in an upright position with feet and thighs parallel to the floor and the upper body in a vertical position. Calibration took 5 seconds and a maximal deviation of 15 degrees in each direction was allowed. No individual calibration such as the activity type or speed of walking or running is necessary. Figure 2B shows a drawing that demonstrates the position of the sensors on a subject.

During the walking and running tests, a light, carried in a backpack strapped securely to the subject, signaled a series of light sensors installed evenly (5-meter intervals) along the track ceiling, leaving the initial and final 5-meter distance for speed transition. Signals from the light sensors, recorded by a cable to a computer, allowed accurate calculation of time of walking and running between sensors; thus, the walking and running speeds were precisely determined.

Protocol

The study consisted of two protocols: a posture and limb movement protocol and a gait protocol. The ability of IDEEA to identify the 5 primary postures, 22 secondary postures, and 5 limb movements was tested by those timed protocols. One of the investigators demonstrated each posture to the subject before the test. After placement and calibration of the device during sitting, the subject was asked to assume each of the prescribed postures for 10 seconds. The investigator, using a stopwatch accurate to 1/100th of a second, then timed the activities and indicated when to change to the next activity. A second investigator simultaneously announced and demonstrated each activity. Each subject was tested by two different sequences of the 22 postures and 5 limb movements.

For gait testing, subjects walked and ran on a 60-meter track at slow, normal, and fast speeds at rates determined by the subjects. After walking and running on the track, subjects were instructed to climb and descend a flight of stairs three times (total, 48 steps) at speeds with which they felt comfortable (normal, fast, then normal again).

The protocol was approved by the Institutional Review Board at St. Luke's–Roosevelt Hospital Center, and subjects signed written consent to participate. The consent forms for subjects under age of 18 were signed by their parents, and those subjects were accompanied by their parents during the test.

Data Analysis

After each test, the data were downloaded and processed on a personal computer, generating a table containing six columns of data for each activity: time, type of PA, speed, power, energy expenditure (EE), and duration of the activity, respectively. Each row represents the specific time-point at which one type of PA changed to another.

The protocol required subjects to assume each posture or limb movement for 10 seconds. Transition time between postures required no more than 4 seconds. We therefore discarded the first 4 seconds to ensure completion for even the most complex transition by the slowest person and, after discarding 1 additional second, used the remaining 5 seconds to estimate the accuracy of the device, which was determined by observing and recording activities by two researchers during tests and comparing results between the device outputs and recordings.

For each subject, we calculated an average correct identification score for each of the 32 types of PA (22 types of postures, 5 types of gaits, and 5 types of limb movements without locomotion). The intra-class correlation was used to compare accuracy for all PA classified in this study with subject characteristics [age, gender, and body mass index (BMI)]. Thus, accuracy = (time of correct activity identification)/(maximal possible time for correct activity detection). A pooled correlation between actual speed and predicted speed was calculated using Fisher's Z transformation. Basic descriptive statistics by overall, gender, and BMI were calculated (Tables 2 and 3).

Results

Posture and Limb Movement Identification

Of the 76 subjects, 68 participated in the tests for posture and limb-movement identification. The overall average of correct identification rate of all postures for 68 subjects was 99% (range, 90.3% to 100.0%) (Table 2). After grouping the secondary postures by the corresponding primary postures, we found "reclining" to be the most difficult group to identify (96.2%), whereas "lying down," "sitting," "standing," and "leaning" were all accurate to >99% (range, 99.2% to ~99.5%). Limb movement without locomotion was correctly recognized at an average rate of 99.2% (97.8% to ~100%). Measurement accuracy of the system was not significantly affected by age ($p = 0.511$), gender ($p = 0.372$), or BMI ($p = 0.078$).

Gait Identification

Among 76 subjects, 69 participated in the tests for gait identification and speed estimation of walking (slow, normal, and fast) and running (slow, normal, and fast). Gaits were correctly detected at an average rate of 98.5% (96.6% to 99.7%) (Table 3). Relatively lower rates of correct classification were found for jumping (96.6%), stair-gaits (98.24%), and running (98.99%), whereas walking was detected at a rate of 99.7%. There was no statistically significant effect of age ($p = 0.135$) or gender ($p = 0.309$). However, there was a significant effect of BMI ($p = 0.045$). Further examination found that BMI was only negatively correlated with running detection rate ($r = -0.25$, $p = 0.031$), but not with walking ($p = 0.111$), descending stairs ($p = 0.238$), or ascending stairs ($p = 0.072$). However, the correlation between BMI and running gait detection rate was very low (-0.25), and the p value ($p = 0.031$) was almost in the boundary ($p = 0.05$) for statistical significance. Actual correct running gait detection rates were >99% for both those above and below a BMI of 25 kg/m^2 (Table 3). This means that the measurement accuracy of the system, in fact, was not greatly affected by BMI.

Speed Prediction of Walking and Running

The average accuracy of the speed estimation of walking and running by IDEEA for 69 subjects is 100.0 ± 3.6% (mean ± SD), ranging from 91.6% to 108.0%. The results show the close match between predicted speed and actual speed. The pooled correlation by using Fisher's Z transformation between actual speed and predicted speed for 69 subjects was found to be 0.986 (individually ranging from 0.935 to 0.995; $p < 0.0001$).

Of total 15,676 steps evaluated, average actual speed was 4.089 ± 2.013 miles per hour (mph) (mean ± SD), whereas average IDEEA-predicted speed was 4.093 ± 1.976 mph (mean ± SD). Overall average error was 0.004 ± 0.324 mph, whereas overall average absolute error was 0.223 ± 0.236 mph.

Discussion

In our standardized protocol, we found an overall rate of 98.7% for the correct identification of 32 types of PA. These results are satisfying, especially in view of the short time period (5 seconds) that was used for the analysis of the "posture" part. We are aware that, by limiting the maximal possible time for correct detection, we decreased the estimated rate of accuracy; however, we did so to perform a highly standardized data analysis. In addition to the overall high rate of PA identification, IDEEA was able to correctly determine duration and intensity of walking or running (correlation factor for speed = 0.986; $p < 0.0001$). Some results of our study, however, require closer examination. A greater number of errors were recorded among leg positions within the primary posture "recline" than for other postures. One difficulty for correct identification of this posture might be the great anatomical differences among our heteroge-

Table 2. Identification accuracy of postures and limb movements

Primary/secondary	Accuracy				
	Overall (%)	**Male (%)**	**Female (%)**	**BMI < 25 kg/m^2 (%)**	**BMI ≥ 25 kg/m^2 (%)**
Sitting					
Upright (normal)	99.7	100.0	99.5	100.0	99.2
Left leg over right leg	99.2	98.2	100.0	100.0	97.9
Right leg over left leg	99.3	98.5	100.0	98.9	100.0
Elbows on knees	98.8	97.2	100.0	100.0	96.8
Left heel up	99.3	100.0	98.8	100.0	98.3
Right heel up	100.0	100.0	100.0	100.0	100.0
Both heels up	99.3	100.0	98.8	98.9	100.0
Both feet elevated	98.7	98.5	98.8	98.9	98.3
Average	99.3	99.1	99.5	99.6	98.8
Standing					
Upright (normal)	98.7	100.0	97.7	98.9	98.3
Left foot on a step	100.0	100.0	100.0	100.0	100.0
Right foot on a step	99.7	99.2	100.0	99.5	100.0
Average	99.5	99.7	99.2	99.5	99.4
Reclining					
Both feet on the ground	94.6	95.5	94.0	94.5	94.8
Left leg over right leg	98.3	98.7	98.0	98.1	98.5
Right leg over left leg	95.8	97.0	95.0	95.4	96.6
Average	96.2	97.1	95.7	96.0	96.6
Leaning					
Left shoulder against wall	98.6	100.0	97.6	97.8	100.0
Right shoulder against wall	100.0	100.0	100.0	100.0	100.0
Two elbows on a counter	99.3	98.5	100.0	98.9	100.0
Average	99.3	99.5	99.2	98.9	100.0
Lying down					
Facing up	100.0	100.0	100.0	100.0	100.0
On right shoulder	99.2	99.4	99.2	98.9	99.8
Facing down	99.3	100.0	98.8	98.9	100.0
On left shoulder	99.3	100.0	98.8	98.9	100.0
Average	99.5	99.9	99.2	99.2	99.9
Limb movement					
Sit, move left leg	99.6	99.8	99.5	99.5	99.8
Sit, move right leg	100.0	100.0	100.0	100.0	100.0
Sit, move both legs	97.8	98.2	97.5	98.4	96.8
Stand, move left leg	98.9	100.0	98.0	100.0	97.0
Stand, move right leg	99.9	99.8	100.0	99.9	100.0
Average	99.2	99.6	99.0	99.6	98.4
Overall Average	99.0	99.2	98.9	99.0	98.9

Table 3. Gait identification accuracy

Gait	Accuracy Overall (%)	Male (%)	Female (%)	BMI < 25 kg/m^2 (%)	BMI ≥ 25 kg/m^2 (%)
Walking	99.7	99.5	99.9	99.5	99.9
Running	99.4	99.1	99.7	99.5	99.1
Climbing stairs	98.2	98.7	97.7	98.2	98.3
Descending stairs	98.5	99.2	97.6	98.8	98.0
Jumping	96.6	94.1	98.0	97.7	93.9
Average	98.5	98.1	98.6	98.7	97.8

neous group of subjects. The trunk sensor has to be attached on the sternum, preferably just below the sternal angle, that is supposedly perpendicular to the vertical axis of the upper body. This sensor represents the angle of the upper body in relation to the four leg and foot sensors and the floor. Its correct alignment is crucial for distinguishing between sitting, reclining, and lying down. Obviously, the body shape of male and female or lean and obese subjects varies considerably in this location of the body. It is therefore difficult to distinguish between the range of angle determined by differences in body shape and the point at which one posture changes into another (e.g., sitting to reclining). Optimization of this sensor fixation and/or redefinition of the threshold angles may improve these results.

Relatively lower rates of correct detection were also found in the "gait" group. In this subset of PA, "jumping" seems to be more difficult to identify (96.6%). We observed that most of the errors were caused by incorrect identification of jumping as "leg movement while standing." This is not too surprising given that every jump is initiated by a leg movement. Further definition and validation of this type of PA is needed. Despite a high rate of proper gait detection in general (98.5%), the correct separation of climbing (98.2%) or descending (98.5%) stairs was slightly lower than for normal walking. This is because the first step on a stair is very similar to a walking or running gait, making it particularly difficult to identify. Again, redefinition of threshold angles used to distinguish a stair gait from a normal walking gait would improve the rate of correct detection. The device did accurately identify walking and running at a rate of 99.7% and 99.4%, respectively. Age and gender did not affect the measurement accuracy, but BMI was a factor for the measurement of running gait.

The major difference between IDEEA and existing devices lies in its ability to intelligently integrate information from multiple sensors and to provide direct results—the type, frequency, duration, and intensity of PAs—that are easier to understand and use. The most obvious shortcoming of IDEEA is that it does not measure arm movements directly. Although it detects locomotion well (such as walking or running), activities involving mainly arm motion, such as rowing, swinging a ball or bat, operating a vacuum cleaner, etc., would not be correctly identified. Whereas the weight and size of existing devices make them difficult to be placed on limbs or feet, the small size and weight of the IDEEA sensors makes multiple placement possible, so this limitation could be corrected by placing additional sensors on the arms. The inconvenience of wearing multiple sensors could be reduced by development of a wireless communication to the data collection device in the future.

Although the types of activities classified in this study cannot represent complicated real-life situations, we tried to identify the most common types of daily PAs, modeled them one by one, and pieced them together to form more meaningful activities such as walking, stair climbing, and jumping. In actual conduct of the experiment, we provided two test cases for each subject, with the same type of activities but completely different sequences. The results showed no difference; all had high accuracy. The prediction of EE by IDEEA has not yet been validated, although a large amount of research and modeling work has been done using its unique ability to derive EE from the type and particularly the intensity (e.g., the speed of walking, running, and step climbing) of activities measured. Future studies will focus on improving the measurement of additional activities and determining the accuracy of extrapolating EE assessments from its measurements.

Although this study did not include tests of cycling, uphill or downhill walking, or running, it did find that IDEEA was able to accurately identify and quantify the most common types of PAs observed in free-living humans. Researchers have a long history of struggling for effective assessment of duration, frequency, type, and intensity of human daily PA (10,20–22). The results from our study suggest that IDEEA is able to systematically classify and measure the most common daily human PAs. The detailed study of PA that IDEEA permits should prove to be useful to many applications including: obesity, anorexia, movement disorders, joint disease, rehabilitation, attention deficit disorder, and neurological disorders. There are other potential applications including gait analysis, disturbances of stance and body balance (e.g., caused by medication, surgical treatments, or simply by aging), personal fitness evaluations, evaluation of workload and its duration, and frequency and intensity of various types of jobs and training, as well as performance analysis for amateur athletes and elite professionals during their sports/exercises testing. IDEEA could be used in a variety of settings including hospitals/clinics, research institutes, fitness clubs, sports training, and military training, as well as by individuals who are interested in personal fitness, body weight control, and general well-being.

Acknowledgments

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