Physical activity recognition using a wearable accelerometer : new perspectives for energy expenditure assessment and health promotion

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Physical activity recognition using a wearable accelerometer

New perspectives for energy expenditure assessment and health promotion

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The research presented in this thesis was carried out at the Human Biology department of the Maastricht University and at the Care and Health Applications Group of Philips Research Laboratories Eindhoven.

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To my Country, Italy
and to the memories of a wonderful youth

Chapter 1

Introduction

Physical activity can be defined as any voluntary body movement generated by the contraction of skeletal muscles resulting in energy expenditure (1). As early as in the Hellenistic period, about five centuries before Christ, when epidemiological research and statistical methodologies did not exist, the Greek physician and philosopher Hippocrates recognized the link between regular physical activity and health (2). He stated that the right amount of physical activity and exercise is the "safest way to health". Scientific support for the belief that physical activity could prevent or ameliorate diseases did not emerge until the 20th century; however, investigation of that possibility began earlier. In 1713, an Italian physician, Ramazzini, wrote "*De morbis artificum diatriba*" (Diseases of workers), the first published work on occupational diseases. He observed that messengers suffered from fewer health problems than cobblers and tailors and recommended to sedentary workers to be more physically active (3). Nowadays, the crucial role of a physically active lifestyle for maintaining and improving physical, physiological, and psychological health is recognized internationally (4, 5). Regular participation in physical activity is associated with numerous health benefits essential for reducing the risk of noncommunicable diseases and adverse health conditions, such as type II diabetes (6-9), cardiovascular diseases (10-12), osteoporosis (13), and breast and colon cancer (14). Furthermore, physical activity results in energy expenditure, which plays a fundamental role in the regulation of body weight and the development of obesity (15), currently an epidemic of global concern (16, 17).

The prevalence of obesity in the United States is 32% among adult men and 37% among adult women (18), and is rising in countries throughout the world, reaching 20% to 30% in some European countries and 70% in Polynesia (16). Obesity represents a strong risk factor for developing many diseases, such as diabetes, cardiovascular diseases, hypertension, and cancer; this is one of the reasons why obesity is considered one of the most serious public health challenges (19). Strategies for disease prevention and health promotion often include guidelines on lifestyle changes that encourage participation in physical activity (4, 5, 16). However, increasing physical activity in obese individuals is problematic because of the high metabolic costs that subjects have to sustain. Indeed, obese individuals are normally less physically active and spend more time sitting than age-matched lean controls (20, 21), but the energy expenditure for physical activity is not significantly different (22-24). The reason is that the metabolic cost of many activities, such as weight-bearing activities like walking (25), and light-intensity activities (26), is proportional to body weight. Thus, obese subjects consume significantly more energy than lean ones in performing the same physical task. This indicates that increasing physical activity in obese subjects is challenging because of the related high rates of energy expended due to the excess body weight.

In this context, objective and accurate measurements of physical activity and of the related physiological responses are urgently needed to make it possible to design successful intervention strategies for increasing physical activity and to establish what dose of physical activity is necessary for obtaining a specific health benefit (27-29). This would certainly help us to beat the global challenge of reversing the epidemic spread of adverse health conditions related to low levels of physical activity.

How to measure physical activity

Physical activity is a multi-dimensional behavior characterized by several aspects, such as duration, intensity, frequency, and type. A variety of methodologies has been developed to measure physical activity in the field and to analyze the relationship between physical activity and health outcomes (27). These can be divided into subjective and objective methods. The subjective methods include direct observations (30), diaries (31-33), activity logs (31), recall (31, 32) and questionnaires (32, 34). They are very popular methods for quantifying physical activity in large-scale studies, because of their relatively low cost. However, subjective methods often provide a biased assessment of physical activity and cannot explore all the diverse aspects of physical activity. Objective methods can measure physiological (metabolic cost, heart rate, body temperature) (27, 35) or biomechanical (acceleration, displacement) effects associated with physical activity (27, 36-38). They generally provide a reliable assessment of physical activity, but since they require the use of specific measuring instruments their applicability in large studies is often limited.

Ideally, physical activity should be measured using objective techniques in free-living conditions, for a period of time representative of the habitual activity level, with minimal discomfort for the user, and with inexpensive systems. Accelerometers reasonably satisfy these requirements, and therefore have been widely used in field research and clinical trials for the assessment of physical activity (36, 38, 39).

Accelerometers

Accelerometer-based activity monitors, often called accelerometers, are portable sensor systems able to quantify physical activity by measuring the acceleration of the human body during movement. Accurate and unobtrusive measurements of physical activity are achieved only when the accelerometer has certain physical and technical characteristics in terms of dimensions, weight, and amount of information processed and recorded. Considering that there is a trade-off between the energy consumption, portability, and performance (quality or quantity of information collected) of an activity monitor, the design largely determines the degree of accuracy and unobtrusiveness.

Accurate measurements of physical activity can be achieved when the acceleration signal from the body is collected at a frequency sufficient to ensure that the full range of human motions is captured. The frequency content of the acceleration of the body during physical activity varies according to the measurement location. At the waist level, 95% of the variability of the acceleration signal can be determined by harmonics within 10 Hz (36, 40), and it has an amplitude that does not exceed 6g in magnitude (1g = 9.8 m/s^2) (36). Thus, an accurate accelerometer should collect acceleration data at a sampling frequency of 20 Hz (according to the Nyquist theorem). Furthermore, it should be able to process the acceleration signal to filter out noise and extract relevant characteristics from the acceleration pattern so as to describe all the aspects of physical activity. This requires complex and frequent operations computed by the accelerometer's processing unit, which increases energy consumption, thus shortening battery life.

Unobtrusive monitoring is achieved when the accelerometer does not interfere with the subject's normal behavior. Small dimensions, lightweight, integrated systems (as opposed to distributed systems) and long operational lifetime are crucially important for unobtrusive monitoring. However, small, lightweight devices usually have a short battery life, because the amount of energy that the battery can provide is directly proportional to its volume and weight (41). The operational lifetime can be defined as the minimum between the battery life and the time to fill up the data storage unit. Unobtrusive accelerometers should support an operational lifetime of several days (42, 43); to determine habitual physical activity the actual number of days required is 3–5 days in many adult populations (43), though in children a longer wearing time might be necessary as the variability in day-to-day physical activity is higher (44). This implies that the accelerometer should work continuously without the battery having to be recharged or the memory having to be emptied before the end of this time interval. This would improve subjects' affinity with the measuring system and reduce interference with their normal activity pattern.

Piezoelectric accelerometers

The first generation of accelerometers consisted of a single site device equipped with one or more piezoelectric acceleration sensors, with dimensions ranging from 7 to 120 cm^3, weight from 17 to 50 grams, and the ability to measure physical activity continuously from 9 to 45 days, depending on the accelerometer (45). A few of the most commonly used activity monitors are the Actigraph (Actigraph, Pensacola, FL), the RT3 (StayHealthy, Monrovia, CA), the Actical (Philips Respironics, Chichester, UK), and the Tracmor (Philips Research, Eindhoven, The Netherlands). These accelerometers are relatively small and lightweight, and their operational lifetime is sufficient to record physical activity over periods of time representative of the habitual activity level. This was often accomplished by limiting the amount of information extracted from the sensed acceleration signal. Physical activity is assessed by determining activity counts (Equation 1), which is the rectified and integrated acceleration signal in a time interval (T) of usually one minute (36) (Figure 1).

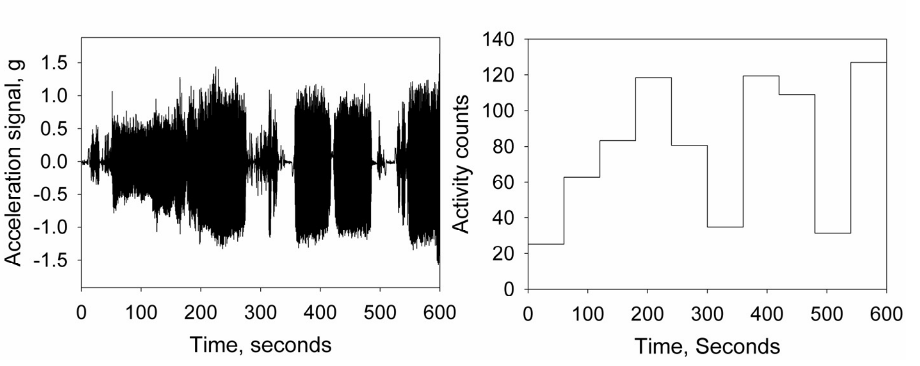

Figure 1. Vector magnitude of the acceleration signal recorded with a piezoelectric accelerometer and the resulting activity counts per minute.

$$Activity\ Counts = \int_{t=t_0}^{t_0+T} |a_x|\, dt + \int_{t=t_0}^{t_0+T} |a_y| dt + \int_{t=t_0}^{t_0+T} |a_z|\, dt \qquad \text{[Equation 1]}$$

Measuring activity counts over time can be used to quantify the duration, frequency and intensity of physical activity. The disadvantage of using activity counts as output from the accelerometer is that the integration process involved in the calculation diminishes the details of the signal within each time window, and this reduces the ability to determine the physical activity pattern and the types of activity performed. Another disadvantage of these accelerometers is that they are equipped with piezoelectric sensors, which do not allow the detection of orientation of body parts or of static activities, as they cannot measure static forces, only dynamic ones caused by movement (45).

Piezoresistive and capacitive accelerometers

The advances in sensor technology and the low-cost mass production of micro electro machined systems (MEMSs) that have occurred in the past 15 years have enabled the development of activity monitors based on piezoresistive or capacitive acceleration sensors. These sensors are sensitive to both static and dynamic forces acting on the system, and are based on the principle of the change in resistance or capacitance in proportion to the acceleration caused by the applied forces (46). Unlike piezoelectric sensors, piezoresistive and capacitive ones are passive components and require an external power source. This means that the critical aspect of portable accelerometers based on piezoresistive or capacitive technology is the operational lifetime, since the battery life is reduced by the sensor’s energy consumption.

Despite this limitation, interest in studying piezoresistive and capacitive sensors has been growing in physical activity research because of the ability of such systems to detect static postures like lying down, sitting, and standing, which are important components of individuals’ activity behavior and cannot be distinguished using piezoelectric sensors (45). Indeed, measurements of static forces allow assessment of the inclination of the body from the vertical during static periods and the definition of body postures. Moreover, some of the more advanced portable systems based on piezoresistive or capacitive technologies have increased data processing and data storage capacity compared to the first generation of accelerometers. They can record the raw acceleration signal for off-line processing, or directly execute complex calculations to extract a rich amount of information from the acceleration signal for on-board analysis (Figure 2). The temporal pattern of specific characteristics of the acceleration signal is often analyzed using activity recognition techniques for the assessment of type, duration, frequency, and intensity of physical activity.

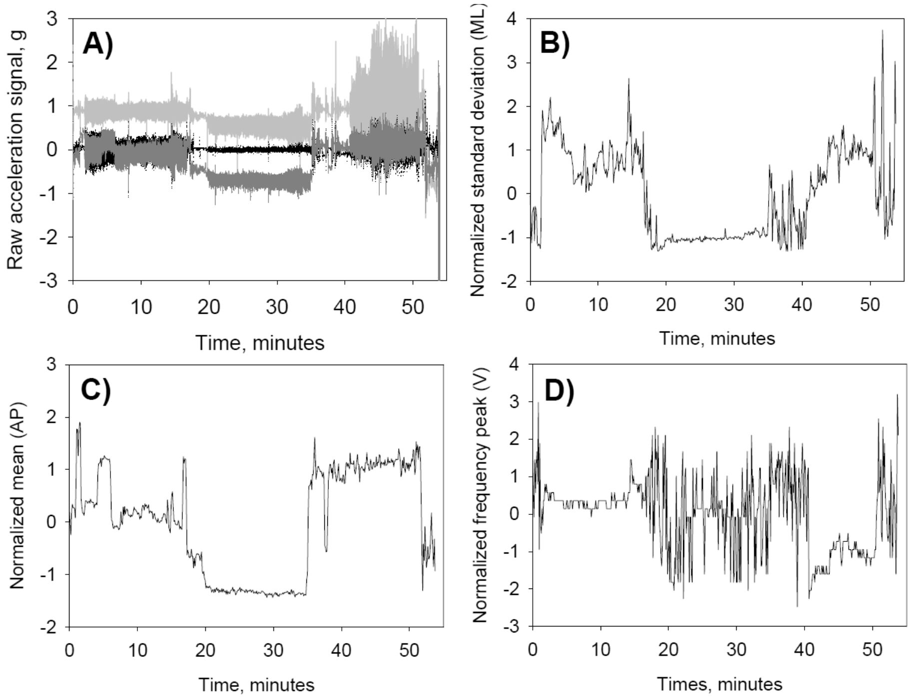

Figure 2. A) Acceleration signal recorded by a capacitive accelerometer for each sensing axis during cycling, rowing, and exercising on an elliptical trainer. B) Normalized standard deviation of the acceleration signal measured in the medio-lateral direction of the body (ML). C) Normalized mean of the acceleration signal measured in the antero-posterior direction of the body (AP). D) Normalized frequency peak of the acceleration signal power spectrum measured in the vertical direction of the body (V).

The most widely studied of these activity monitors are the MiniMod (McRoberts, The Hague, The Netherlands), the ArmBand (BodyMedia, Pittsburgh, PA), and the latest version of the Actigraph (Mod: GT3X; Actigraph, Pensacola, FL). Besides these single-site accelerometers, other multiple-site activity monitors based on passive sensors have been presented in the literature: the Intelligent Device for Energy Expenditure and physical Activity (IDEEA) (47), the Physical Activity Monitoring System (PAMS) from James Levine's research group (21, 48), the Wockets activity monitor from Stephen Intille's research group (49), and the activity monitor from Henk Stam's and Hans Bussmann's research group (50, 51). Piezoresistive and capacitive accelerometers are usually less unobtrusive than piezoelectric ones, have a shorter battery life and are often not integrated in a single device, but their accuracy is much higher as they can monitor all the multiple aspects of physical activity.

Physical activity recognition

An objective and automatic method for assessing physical activity types in free-living conditions remained unavailable for many years because of the lack of accelerometers capable of measuring sufficiently detailed information regarding body acceleration. Recent advances in activity monitoring technology and data recording, and the introduction of piezoresistive and capacitive accelerometers have been followed by the development of physical activity recognition techniques entailing the automatic detection of physical activity types by solving a pattern classification problem. A pattern classification system consists of a sensor that gathers information about the object to be classified, a feature extraction mechanism designed to compute the information collected with the sensor, and a classification model that processes the features using the knowledge contained in a machine learning algorithm and identifies the pattern under investigation (52).

Physical activity recognition based on accelerometers has emerged in recent years as a topic of interest in a number of different fields, from health-related research to pervasive computing. The complexity of the classification problem, which depends on the number of activity types to be identified, is directly related to the amount of information that the accelerometer needs to collect to solve it. Although activity recognition has been attempted by using features extracted from the activity counts time series (53, 54), most of the research on accelerometer-based activity classification has been based on features of the raw acceleration signal recorded at a frequency of more than 20 Hz (47, 49-51, 55, 56). The features considered for activity recognition can have different degrees of complexity, and there is no indication of which features should be used to solve a specific classification problem. From the acceleration signal different feature types can be extracted. There are heuristic features which are derived from an intuitive understanding of how a specific movement will produce a certain accelerometer output. For example, the angle of orientation of the accelerometer from the vertical can be used to differentiate between static postures (57, 58) and postural transition (59). The features can also be calculated in the time domain, and consist of statistical values describing the temporal distribution of the acceleration signal (49, 60, 61), or they can analyze the signal morphology (51). Additionally, spectral features can be determined by analyzing the fast Fourier transform (FFT) of the acceleration signal to describe how the variability in the acceleration signal is distributed in the frequency domain (49, 62). Features with increased complexity are based on the wavelet transform of the signal (63, 64), which has been proposed to detect transitions between activities. The features are often calculated in discrete time intervals, also called windows. The length of these time windows can determine the resolution of the classification method, because a classification algorithm is applied to each of the windows separately.

After a set of features has been computed from a temporal window of the acceleration signal, an activity category is associated with it based on the knowledge contained in a classification algorithm. Many classification algorithms have been proposed for physical activity recognition. Their degree of complexity varies from simple threshold-based schemes and decision tree classifiers to more advanced algorithms, such as artificial neural networks or hidden Markov models (52). The knowledge of the classification algorithms is represented by a series of rules based on the acceleration features which are learned during the training phase of the algorithm.

Almost all previous studies of physical activity recognition differ by the type and number of activities identified and by the location, type and number of accelerometers used. Studies based on distributed accelerometer systems showed very high classification accuracy for the detection of postures and different types of ambulatory and cycling activities (49). Zhang et al. (47) showed that the IDEEA, an activity monitor made up of 5 distributed sensors, had a classification accuracy of more than 98% for recognizing 32 types of activity and posture using an artificial neural network. Bussman et al. (65-68) reported that the activity monitor developed by their research laboratory, consisting of 4 acceleration sensors placed in different body locations, had an agreement rate of 89 – 90% with video observation in detecting a series of nine dynamic movements and different types of posture using hierarchical and Boolean classifiers. Bao and Intille (49) showed that from a set of five accelerometers placed on different body parts a classification accuracy of 84% could be achieved for identifying 20 common activity types with a decision tree classifier. However, when two of the five accelerometers were used (located on the wrist and thigh) the classification accuracy dropped by only 4%. Despite the obvious advantage for physical activity recognition provided by the use of distributed systems to measure the acceleration of different body parts, there are practical limitations on the number and location of accelerometers that the subjects can tolerate. For this reason, activity recognition schemes have been developed based on a single accelerometer. Pober et al. (53) reported an accuracy of 81% for identifying walking and certain lifestyle activities, like vacuuming and working on a computer, by applying a hidden Markov model to the acceleration signal recorded using an Actigraph accelerometer. Ermes et al. (55) showed that using either a decision tree or an artificial neural network the acceleration signal recorded with a tri-axial accelerometer could be used to recognize nine types of activity such as sports, walking and sedentary activities. The classification accuracy was between 80 and 90%; however, measuring the acceleration at the wrist did not allow a distinction to be made between sitting and standing postures.

How to measure energy expenditure

The total amount of energy expenditure (TEE) consists of three main components: basal energy expenditure (BEE), diet-induced thermogenesis (DIT) and activity-related energy expenditure (AEE) (Figure 3). BEE is the energy expenditure necessary to sustain and maintain the integrity of vital functions. BEE is mainly determined by body composition and by the amount of lean tissue which represents the metabolic active mass of the body. BEE can be divided into sleeping metabolic rate (SMR) and the energy cost for arousal. A few authors reported that SMR is on average 5 to 10% lower than BEE (69, 70). However, Wouters-Adriaens et al. (71) showed that SMR and BEE are not significantly different in young adults. DIT is the energy expenditure for the digestion, absorption and conversion of food and is estimated to be 10% of TEE in subjects consuming a mixed diet (72). AEE reflects the energy cost associated with physical activity and body movement. It is a direct function of all the metabolic processes involved with the exchange of energy required to support the skeletal muscle contraction during physical activity. AEE is not only a function of the intensity, duration and type of physical activity but also of the mass of the body displaced during movements. To compare AEE between subjects, therefore, adjustment for body weight is necessary, but which correction method should be used has not yet been defined (26, 73). Physical activity is often quantified from TEE by defining the physical activity level (PAL), which can be calculated as TEE divided by SMR.

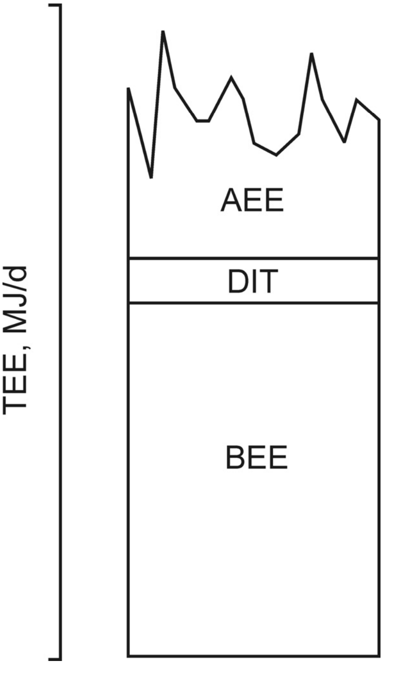

Figure 3. Components of total energy expenditure (TEE): Basal energy expenditure (BEE), diet induced thermogenesis (DIT), and activity energy expenditure (AEE).

Accurate assessment of TEE is necessary in order to investigate the dose-effect relationship between physical activity and physiological response. TEE can be assessed using indirect calorimetry, which is based on measurements of oxygen (O_2) consumption and carbon dioxide (CO_2) production to quantify the amount of substrate oxidation (carbohydrates, lipids and proteins), and energy expenditure.

Measurements of TEE using indirect calorimetry can be performed using portable systems, a whole-room calorimeter, or doubly-labeled water.

Portable indirect calorimeters have recently been developed, such as the K4 (Cosmed Inc., Chicago, IL), the Vmax29 (SensorMedics, Viasys Systems, Bilthoven, The Netherlands), and the VO2000 (Aereo Sport Inc., St. Augustine, FL) (74). They allow field assessment of O_2 uptake, from which energy expenditure can be estimated based on the assumed relationship between O_2 consumption and the caloric cost of substrate oxidation (35, 75). However, issues pertaining to costs, cumbersome and obtrusive instrumentation, altered patterns of physical activity, and the lack of well-established validity and reliability in a variety of field settings limit the usefulness of this approach in physical activity research.

The whole-room calorimeter, often called respiration chamber, is an air-tight room in which O_2 consumption and CO_2 production are continuously measured by analyzing the differential concentration of gas between the air flowing into and out of the chamber. The respiration chamber used in this thesis measured 14 m^3 and was equipped with a bed, washing bowl, freeze toilet, table, chair, computer, and other entertainment equipment (76). TEE and its different components can be measured in the respiration chamber; however, because of the confined environment, AEE is not representative of free-living AEE.

The doubly-labeled water method is the gold standard technique for measurements of TEE in daily life (77). It consists of the stable water isotopes ^2H_2O and $H_2{}^{18}O$, and is administered to subjects as a liquid that is dosed according to body size. As a consequence of metabolic processes, ^2H is eliminated in the form of H_2O, while ^{18}O is eliminated as H_2O and CO_2. The concentration of both isotopes can be measured in urine, saliva, or blood samples and the difference in the two elimination rates is a measure of the CO_2 production, from which oxygen uptake and energy expenditure are extrapolated using established equations (78). Although doubly-labeled water provides precise estimates of free-living energy expenditure, this technique is expensive and requires sophisticated equipment for the spectrometric analysis of body fluids.

Estimation of energy expenditure using accelerometers

The acceleration of the body is theoretically proportional to the muscular forces responsible for movement and thus to energy expenditure. Based on this principle, accelerometers have been tested against indirect calorimetry to determine whether measurements of physical activity duration and intensity (activity counts scored over time) can reliably estimate energy expenditure. Several studies have focused on the use of linear regression techniques to develop equations to predict PAL, or the metabolic cost of physical activity (MET = TEE/resting energy expenditure), from activity counts. TEE and AEE have then been determined from PAL, with basal or resting energy expenditure and the value of DIT being known. Prediction equations of TEE and AEE have also been developed using multiple-linear regression techniques to include activity counts and parameters descriptive of body size (length, weight, BMI) or body composition (fat and lean mass) as independent elements of the model. Many accelerometers have been tested under laboratory conditions during standardized activities using a portable calorimeter or in a respiration chamber. The prediction accuracy of PAL or MET varied according to the device and the test conditions. The correlation coefficient between activity counts measured with the Actigraph and MET for walking was between 59% and 86% (79). Bouten et al. (15) reported that Tracmor activity counts can predict PAL during walking with an accuracy of 95%. However, during sedentary activities the accuracy dropped to 67%. Laboratory tests have shown that prediction equations developed during ambulatory activities were not adequate to describe the relationship between activity counts and the metabolic cost of sedentary and lifestyle-related activities (80, 81). Considering that accelerometers should be able to describe the energy cost of any type of activity performed in daily life, validations in free-living conditions have also been done by comparing measurements of activity counts to doubly-labeled water. Recent reviews (38, 82) reported that only a few of the accelerometers can accurately estimate TEE and AEE in free-living conditions, and subjects' characteristics are often the only significant contributors to the explained variation in TEE or AEE of the prediction models. The Tracmor accelerometer was found to provide an accurate estimate of energy expenditure in both laboratory and free-living conditions, as the measured activity counts significantly contributed to the explained variation in TEE, AEE, and PAL in the prediction models developed (83, 84).

Outline of the thesis

This thesis is focused on analyzing the potential advantages offered by accelerometer-based physical activity recognition to improve the assessment of energy expenditure and understanding of the relationship between activity behavior and health. Firstly, a novel version of the Tracmor accelerometer was tested against doubly-labeled water to report the accuracy of activity counts in predicting energy expenditure (**Chapter 2**). Compared to activity counts, more detailed information on physical activity can be extracted from the raw acceleration measured with Tracmor. Based on recordings of raw acceleration data, models were developed to detect activity types, duration and intensity by using physical activity recognition techniques (**Chapter 3**). Applying such classification algorithms to daily life registrations of body acceleration led the way to objectively determining the activity types performed by subjects. This information was used to investigate whether physical activity recognition techniques could improve the assessment of energy expenditure as compared to activity counts (**Chapter 4**).

The duration of the activity types engaged in daily life determines the activity behavior, and the metabolic expenditure due to physical activity. Using accelerometer-based physical activity recognition, an analysis was conducted of which aspects of the activity behavior were advantageous for achieving a high PAL in an adult population (**Chapter 5**). In addition, the effect of weight loss on the activity behavior and AEE in obese subjects was studied (**Chapter 6**). The use of physical activity recognition techniques provided objective data on the behavioral change associated with a reduction in body weight and the related metabolic consequences. In this way it was possible to quantify how much physical activity was necessary to compensate for the decreased cost of physical activity due to the lower body weight, since high levels of AEE are beneficial for disease prevention and weight loss maintenance. Physical activity recognition was also used to determine which aspects of the activity behavior were significantly associated with markers of cardiovascular health, as determined by heart rate variability analysis (**Chapter 7**). The aim was to examine which activity types could produce a cardio-protective physiological response by triggering metabolic processes, independent of confounding factors such as age and body weight.

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Chapter 2

Estimation of free-living energy expenditure using a novel activity monitor designed to minimize obtrusiveness

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Abstract

The aim of this study was to investigate the ability of a novel activity monitor designed to be minimally obtrusive in predicting free-living energy expenditure. Subjects were 18 men and 12 women (age: 41 ± 11 y, BMI: 24.4 ± 3 kg/m^2). The habitual physical activity was monitored for 14 days using a DirectLife tri-axial accelerometer for movement registration (Tracmor$_D$) (Philips New Wellness Solutions, Lifestyle Incubator, Netherlands). Tracmor$_D$ output was expressed as activity counts per day (Cnts/d). Simultaneously, total energy expenditure (TEE) was measured in free-living conditions using doubly-labeled water. Activity energy expenditure (AEE), and the physical activity level (PAL) were determined from TEE and sleeping metabolic rate. A Multiple-linear regression model predicted 76 % of the variance in TEE, using as independent variables sleeping metabolic rate (Partial-r^2 = 0.55, P<0.001), and Cnts/d (Partial-r^2 = 0.21, P<0.001). The standard error of TEE estimates was 0.9 MJ/d or 7.4 % of the average TEE. A model based on body mass (Partial-r^2 = 0.31, P<0.001) and Cnts/d (Partial-r^2 = 0.23, P<0.001) predicted 54 % of the variance in TEE. Cnts/d were significantly and positively associated with AEE (r = 0.54, P<0.01), PAL (r = 0.68, P<0.001), and AEE corrected by body mass (r = 0.71, P<0.001). This study showed that the Tracmor$_D$ is a highly accurate instrument for predicting free-living energy expenditure. The miniaturized design did not harm the ability of the instrument in measuring physical activity and in determining outcome parameters of physical activity such as TEE, AEE, and PAL.

Introduction

The increasing incidence of obesity represents one of the greatest health challenges of the current century (1). Obesity is a serious threat to health because it increases the risk of developing many chronic diseases, such as diabetes and cardiovascular disease (2). Several studies have highlighted the relationship between obesity and genetic factors (3), biological, socioeconomic, and environmental factors (4). However, the main underlying cause of obesity is represented by a chronic imbalance between energy intake and energy expenditure. Achieving a negative balance between energy intake and expenditure is a key factor to lose weight. This could be realized, for example, by increasing energy expenditure through physical activity. Furthermore, increasing the level of physical activity has been often recommended to improve health and reduce risks for chronic diseases (5). For these reasons, accurate measurements of physical activity and energy expenditure are necessary to define optimal intervention strategies to achieve health benefits.

Several methods have been proposed to monitor physical activity and to determine total energy expenditure (TEE). The gold standard technique for the assessment of TEE in free-living conditions is the doubly-labeled water method (DLW), which is based on indirect calorimetry. However, DLW is markedly expensive and requires appropriate laboratory equipment for samples analysis. Thus, it is infrequently used in large-population studies to assess TEE. Other methods such as diaries and questionnaires (6), heart rate monitors (7), and motion sensors (8) have been proposed to assess physical activity and to estimate TEE. Ideally, physical activity should be accurately measured in free-living conditions, over a period of time representative of the habitual activity level, and with minimal discomfort to the subject. Activity monitors based on accelerometers reasonably satisfy these requirements, and therefore have been used in several studies. Accelerometer output has been often used to estimate, together with subjects' characteristics, the TEE, and the activity energy expenditure (AEE) (9, 10). Furthermore, accelerometers' output is linearly related to the physical activity level (PAL, TEE/sleeping or resting metabolic rate) (10).

Improving the accuracy of accelerometers in predicting TEE, AEE and PAL has been the focus of several studies (11-14). Frequently, the achievement of higher estimation accuracy coincided with the increase in the complexity of the measurement system. For example, network systems of accelerometers, placed in different body parts, have been developed to improve the accuracy in measuring TEE, and AEE (11, 13, 15). Likewise, accelerometers have been coupled to heart rate monitors to increase the accuracy in the AEE estimation (7, 16). However, the performance of these complex systems showed a relatively limited improvement in the estimation error of TEE (10). Furthermore, they have seldom been validated in free-living conditions using, as a reference, DLW. On the other hand, activity monitors used in daily life should be minimally obtrusive. This implies the employment of a simple measuring system, with small dimensions, and characterized by long battery life and memory storage capacity.

This would be beneficial to improve the compliance of the users to the measuring device, and to reduce the interference of the monitoring system with the spontaneous activity behavior. However, unobtrusive accelerometers designed to quantify physical activity using activity counts, often showed poor correlation with AEE and PAL (10).

The current study investigated the ability of a novel accelerometer specifically designed to be minimally obtrusive, the DirectLife tri-axial accelerometer for movement registration (Philips New Wellness Solutions, Lifestyle Incubator, Netherlands), to predict TEE, AEE, and PAL.

Methods

Subjects

The study population was composed of 30 healthy adults (18 men and 12 women). They were recruited by advertisement in local newspapers to participate in the study. Written informed consent was obtained and the study was approved by the Ethics Committee of the Maastricht University Medical Centre.

Table 1. Subjects' characteristics (N = 30).

Parameter	Mean ± SD	Range
N (M/F)	30 (18/12)	
Age, y	41 ± 11	26 – 60
Body mass, kg	74.4 ± 11.9	51.9 – 103.4
Height, m	1.74 ± 0.08	1.58 – 1.89
BMI, kg/m^2	24.4 ± 3.0	19.0 – 31.4
FM, kg	19.4 ± 6.5	8.4 – 33.2
FFM, kg	54.9 ± 8.4	39.4 – 70.2
SMR, MJ/day	6.9 ± 0.8	5.5 – 8.3
TEE, MJ/day	12.1 ± 1.8	8.7 – 15.5
AEE, MJ/day	4.0 ± 1.2	2.1 – 6.4
PAL	1.76 ± 0.17	1.43 – 2.08
$Tracmor_D$, 10^3 Counts/day	1572 ± 450	877 - 2626

BMI, body mass index; FM, fat mass; FFM, fat free mass; SMR, sleeping metabolic rate; TEE, total energy expenditure; AEE, activity energy expenditure; PAL, physical activity level; $Tracmor_D$, DirectLife activity monitor output.

Study design

Subjects reported to the laboratory on day 0 at 09h00 p.m. for an overnight stay in a respiration chamber. Anthropometric measurements were taken in the morning after an overnight fast. Body mass was measured on an electronic scale (Mettler Toledo ID1 Plus, Giessen, Germany) to the nearest 0.01 kg. Height was measured to the nearest 0.1 cm (SECA Model 220, Hamburg, Germany). Body volume was determined by underwater weighing. During the underwater weighing the residual lung volume was measured using the helium dilution technique (Volugraph 2000, Mijnhardt, Bunnik, The Netherlands). Total body water was determined using deuterium dilution, according to the Maastricht protocol (17). Body composition was calculated from body mass, body volume and total body water using the Siri's three-compartment model (18). The study included a two weeks observation period for the measurements of energy expenditure, from the morning of day 1 until the morning of day 15. Simultaneously, physical activity was monitored using a tri-axial accelerometer for movement registration.

Sleeping metabolic rate

Sleeping metabolic rate (SMR) was measured during an overnight stay in the respiration chamber. The room consisted in an airtight chamber with an internal volume of 14 m^3 and was furnished with bed, table, chair, freeze toilet, washing bowl, radio, television, and a computer (19). Energy expenditure was calculated from O_2-consumption and CO_2-production according to Weir's formula (20). SMR was defined as the lowest observed energy expenditure for three consecutive hours during the night. Room temperature was held constant at 20 ± 1 °C.

Energy expenditure

The TEE was measured using DLW according to the Maastricht protocol (17). On the evening of day 0, after the collection of a background urine sample, subjects drank a weighted amount of $^2H_2{}^{18}O$ such that baseline levels were increased with 100ppm for ^2H and 200ppm for ^{18}O. Additionally, urine samples were collected in the morning (from second voiding) of day 1, day 8, and day 15, and in the evening of day 1, day 7, and day 14. The AEE was measured as (0.9 x TEE) – SMR, assuming the diet-induced thermogenesis to be 10% of TEE (21). The mean PAL was calculated as TEE/SMR. AEE was also expressed per kilograms of body mass as commonly proposed to describe physical activity (22-24).

Physical activity monitoring

The habitual PA was assessed using a DirectLife tri-axial accelerometer for movement registration ($Tracmor_D$) (Philips New Wellness Solutions, Lifestyle Incubator, Netherlands, url:http://www.directlife.philips.com), which was based on the research device Tracmor (10, 24). The device is a small (3.2 x 3.2 x 0.5 cm), light-weight (12.5 g) instrument (Figure 1). The $Tracmor_D$ is waterproof up to 30 meters depth, and has a battery life of 3 weeks and an internal memory that can store data for up to 22 weeks. The features of the $Tracmor_D$ have been designed to enhance wearability and reduce the interference of the monitoring system with the spontaneous activity behavior. This has been shown in a study by Goris et al. (25) where the $Tracmor_D$ was used to monitor PA in a population of 217 subjects. After 12 weeks from the start of the monitoring period still 140 subjects were wearing the device on a daily basis. The $Tracmor_D$ is also able to provide feedback to the user on the performed physical activity. An indicator bar of light emitting diodes (LED) activates on demand, showing the achievement of the day in terms of amount of physical activity performed as compared to an optimal target defined based on recent recommendations of the World Health Organization. This function was temporarily disabled by the manufacturer in the $Tracmor_D$ employed in the current study. The $Tracmor_D$ was placed at the lower back using an elastic belt, and the subjects were instructed to wear the accelerometer during waking hours. A diary was used to report periods in which the subject was not wearing the $Tracmor_D$ during the day. At the end of the monitoring period the $Tracmor_D$ was connected to a personal computer and the recorded data were downloaded using dedicated software (Philips New Wellness Solutions, Lifestyle Incubator, Netherlands). $Tracmor_D$ output was expressed as activity counts per minute. The $Tracmor_D$ activity counts per minute were summed over the entire monitoring period and divided by the number of monitoring days to determine the average $Tracmor_D$ counts per day (Cnts/d).

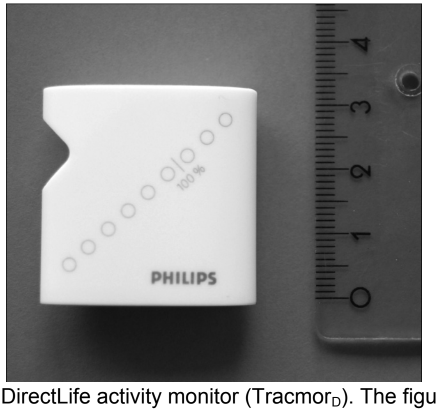

Figure 1. The DirectLife activity monitor ($Tracmor_D$). The figure shows the small dimensions of the instrument (left) as compared to a centimeter ruler (right).

Statistical analysis

Stepwise multiple-linear regression analysis was used to select the best independent variables to predict TEE and AEE. The Cnts/d was the independent variable that was considered to account for differences in physical activity. Additionally, three different sets of independent variables were considered to account for the differences in body size: SMR, basic body characteristics (body mass, height, age, and gender) and advanced body characteristics (fat mass, fat free mass [FFM], age, gender). The independent variables considered in the regression analysis of AEE were the same as in the regression analysis of TEE with the exception of SMR. Simple linear regression was used to develop prediction models for PAL, and AEE scaled to body mass (AEE/kg) using as independent variable Cnts/d. The leave-one-subject-out cross-validation was used to determine the standard error of validation (SEV), representing the performance of the models in estimating TEE, AEE, PAL, and AEE/BM for subjects not used to develop the prediction equations. The Pearson correlation coefficient (r) was used to describe the association between variables. The measured parameters are expressed as mean ± standard deviation. The statistical software SigmaStat (Systat software, San Jose, CA) was used for statistical analysis. The significance level was set to $P < 0.05$.

Results

Physical characteristics of the subjects are presented in Table 1. Subjects wore the accelerometer on average 14.4 ± 1.2 h/day, which was 95 ± 3 % of their waking hours. Measured TEE, AEE, AEE/kg, and PAL are presented in Table 1. The Cnts/d were significantly associated with AEE ($r = 0.54$, $P<0.01$), AEE/kg ($r = 0.71$, $P<0.001$), and PAL ($r = 0.68$, $P<0.001$). No significant association was observed between TEE and Cnts/d ($P = 0.16$).

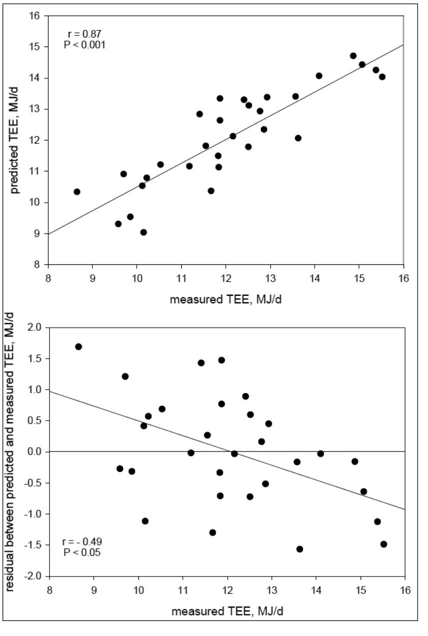

Figure 2. Regression and residual plots of the prediction models of total energy expenditure (TEE) based on accelerometer output and SMR.

Prediction of TEE

The Cnts/d significantly contributed to the explained variation in TEE of each prediction model developed using the multiple-linear regression analysis (Table 2). The model based on SMR and Cnts/d explained 76% (r =0.87) of the variation in TEE, with a standard error of estimate (SEE) of 0.9 MJ/day or 7.4% of the mean measured TEE. The residuals of the model were negatively associated with the measured TEE (r = -0.49, P<0.05) (Figure 2). Considering basic body characteristics and Cnts/d in the stepwise regression analysis, only body mass and Cnts/d were included in the prediction model, and the explained variation in TEE was 54% (r =0.73). The residuals of this model were significantly and negatively associated with the measured TEE (r = -0.68, P<0.001). When advanced body characteristics and Cnts/d were used in the stepwise regression analysis, FFM and Cnts/d were included in the prediction model of TEE. The explained variation in TEE of this model was 68% (r =0.82). The residuals of this model were negatively associated with the measured TEE (r = -0.57, P<0.05). None of the physical characteristics of the population were correlated to the residual of the prediction models. Coefficients, significance level, partial correlations, SEE, and SEV of all models are summarized in Table 2.

Table 2. Prediction models of TEE.

Dep	Ind	Coef	Par-r^2	SD	r^2	SEE	SEV	SEV%
TEE	Int	- 4.00		0.35				
	SMR	1.9**	0.55	0.05				
	Cnts/d	$1.91 \cdot 10^{-6}$**	0.21	$0.06 \cdot 10^{-6}$				
Model					76%	0.90	0.96	7.9%
TEE	Int	0.65		0.4				
	BM	0.11**	0.31	0.004				
	Cnts/d	$2 \cdot 10^{-6}$**	0.23	$0.1 \cdot 10^{-6}$				
Model					54%	1.27	1.35	10.5%
TEE	Int	0.04		0.3				
	FFM	0.17**	0.51	0.005				
	Cnts/d	$1.67 \cdot 10^{-6}$**	0.17	$0.08 \cdot 10^{-6}$				
Model					68%	1.06	1.11	9.2%

Dep, dependent element in the model; Ind, independent elements; Coef, coefficient; Par-r^2, partial correlation; SD, standard deviation; r^2, correlation coefficient; SEE, standard error of estimation (MJ/day); SEV, standard error of validation (MJ/day); SEV%, percentage SEV of the average dependent variable; TEE, total daily energy expenditure; SMR, sleeping metabolic rate; BM, body mass; FFM, fat free mass; Cnts/d, tri-axial accelerometer output. **, P<0.001.

Prediction models of AEE

The Cnts/d significantly contributed to the explained variation in AEE of each developed prediction model (Table 3). Considering advanced body characteristics and Cnts/d in the stepwise regression analysis, FFM and Cnts/d were included in the prediction model. The explained variation in AEE was 53% (r =0.73) with a SEE of 0.82 MJ/d or 20.5%. The residuals of this model were negatively associated with the measured AEE (r = -0.69, P<0.05) (Figure 3). When basic body characteristics and Cnts/d were entered as independent variables in the stepwise regression analysis, body mass and Cnts/d, significantly contributed to the explained variation in AEE. The model explained 46% (r =0.68) of the variation in AEE. The residuals of this model were negatively associated with the measured AEE (r = -0.73, P<0.001). Coefficients, significance level, partial correlations, SEE, and SEV of all models are summarized in Table 3.

Table 3. Prediction models of AEE.

Dep	Ind	Coef	Par-r^2	SD	r^2	SEE	SEV	SEV%
AEE	Int	- 1.89		0.31				
	BM	0.04*	0.30	0.003				
	Cnts/d	$1.8 \cdot 10^{-6}$**	0.16	$0.07 \cdot 10^{-6}$				
Model					46%	0.94	0.88	22%
AEE	Int	- 2.30		0.25				
	FFM	0.07**	0.30	0.004				
	Cnts/d	$1.6 \cdot 10^{-6}$**	0.23	$0.06 \cdot 10^{-6}$				
Model					53%	0.87	0.82	20%

Dep, dependent element in the model; Ind, independent elements; Coef, coefficient; Par-r^2, partial correlation; SD, standard deviation of the coefficient of the model at each step of the cross-validation; r^2, correlation coefficient; SEE, standard error of estimation; SEV, standard error of validation; SEV%, percentage SEV of the average dependent variable; AEE, activity energy expenditure; BM, body mass; FFM, fat free mass; Cnts/d, tri-axial accelerometer output. *, P<0.01; **, P<0.001.

Prediction models of PAL and AEE per kilogram

Simple linear regression was used to develop prediction models of PAL and AEE/kg using Cnts/d, as these represent common measures of physical activity. The model developed to predict PAL showed an explained variation in PAL of 46% (r =0.68, P<0.001). The regression equation was given by:

$$PAL = 1.354 + 256 \times 10^{-9} \times Cnts/d$$

The residuals of the model were negatively associated with the measured PAL (r = -0.74, P<0.001) (Figure 3). The SEE of the models was 0.13, representing 7.4% of the average PAL. The SEV was 0.13. The model developed to predict

AEE/kg explained 50% of the variation in AEE/kg (r =0.71, P<0.001). The regression equation was given by:

$$AEE/kg\ (MJ/day/kg) = 0.0135 + 26 \times 10^{-9} \times Cnts/d$$

The residuals of this model were negatively associated with the measured AEE/kg (r = -0.68, P<0.001). The SEE of the models was 0.012 MJ/day/kg, representing 22% of the average AEE/kg. The SEV was 0.013 MJ/day/kg.

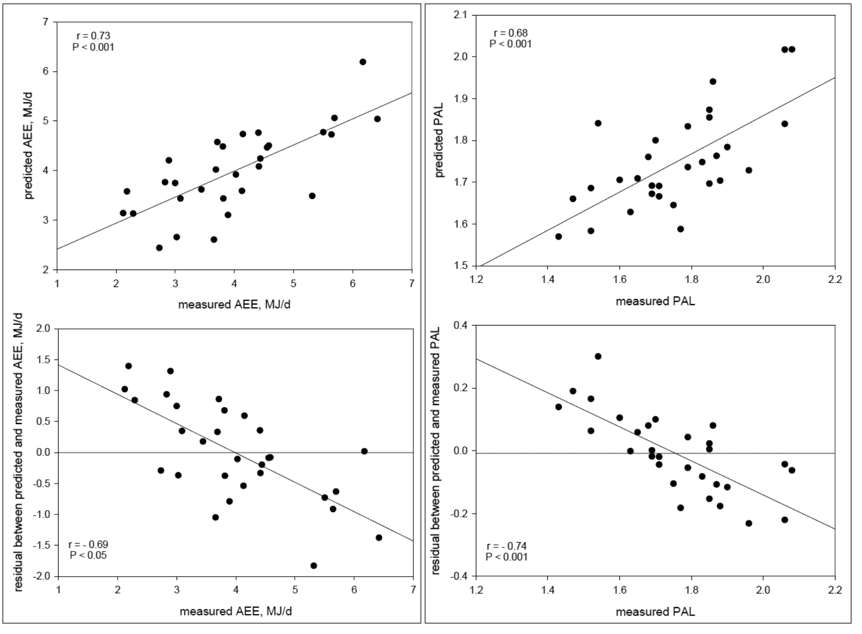

Figure 3. Regression and residual plots of the prediction models of activity energy expenditure (AEE), and physical activity level (PAL) based on accelerometer output.

Discussion

The Tracmor$_D$ is one of the smallest and light-weighted instruments developed to measure physical activity. The design of Tracmor$_D$ was focused to reduce obtrusiveness and to diminish the interference of the measuring system with the individuals' activity behavior. Considering that important specifications of wearable activity monitors, such as the battery life and the on-board processing capacity, are often negatively affected by the miniaturization of the measuring system, we felt it important to test the ability of the Tracmor$_D$ accelerometer in predicting free-living energy expenditure.

The developed models used to predict TEE showed that Cnts/d measured with the Tracmor$_D$ significantly contributed to the explained variance in TEE. In particular, depending on which independent variables were considered to adjust for differences in body size, Cnts/d accounted for 17% to 23% of the explained variance in TEE of the models. Correspondingly, Cnts/d contributed for 16% to 23% to the explained variance in AEE. Furthermore, a direct linear association was observed between Cnts/d and PAL, and between Cnts/d and AEE/kg. Thus, in all developed models the contribution of the $Tracmor_D$ was necessary to achieve a higher accuracy in predicting free-living energy expenditure.

From the residual analysis of the prediction models a significant negative trend was observed. This means that applying the developed models to population of subjects with a very low activity level, and with low levels of TEE, and AEE might produce an overestimation of PAL and energy expenditure. On the other hand, an underestimation of PAL and energy expenditure could be expected in subjects with a very high activity level, and a correspondingly high TEE, and AEE. However, the standard error of estimate of the TEE prediction models observed in the broad range of TEE of the current study was between 7% and 10 %. Furthermore, the study participants covered the range of normal daily life activity levels, as indicated by the measured PAL range which was from 1.43 to 2.08, but they were not highly physically active. Considering that the obtained standard error of estimate in this wide range of PAL was below 7%, we can assume that the observed trend in the residual would not limit the applicability of the PAL prediction model to a population of subjects within the range of normal activity levels. This trend in the residual could be due to an overestimation of the energy cost for sedentary activities that might characterize the behavior of subjects with a low PAL. Likewise, this trend could be caused by an underestimation of the energy cost for high-intensity activities, which might characterize the behavior of subjects with high PAL. However, specific studies are necessary to investigate the performance of the $Tracmor_D$ in measuring energy expenditure for a number of activity types to understand which factors could be imputed of reducing the accuracy of the TEE, AEE, and PAL prediction models.

Only a small number of accelerometers have been validated in free-living conditions against the gold standard technique of DLW. Those that were validated often show poor correlations with energy expenditure or the main contribution to the explained variation in TEE, or AEE was determined by subjects' physical characteristics (10). These prediction performances are summarized in Table 4. Indeed, one of the most popular and most frequently validated accelerometers, the Actigraph (latest size: 5.1 x 4.1 x 1.5 cm; Actigraph, Fort Walton Beach, FL) released in several versions, showed poorer accuracy in predicting TEE, AEE, AEE/kg, and PAL as compared to the $Tracmor_D$ (10, 23, 26, 27). Similarly, prediction models of PAL, and AEE developed for the Tritrac-R3D (size: 12 x 6.5 x 2.2 cm; Hemokinetics, Madison, WI) showed a lower accuracy as compared to the $Tracmor_D$ (10, 28). Furthermore, a recent validation study investigated the ability of several prediction equations developed for the Actigraph and for the Tritrac-R3D to estimate TEE, as measured in free-living conditions using DLW (9). This study concluded that only 2 out of 14 prediction equations showed to produce a prediction of TEE which was non-significantly different from the measured TEE, but a large SEE was still observed (15-17% of the mean TEE). However, it should be noted that these performances could have been worsened by the fact that an independent population was used for testing the accuracy of the prediction equations. Very few studies reported a higher accuracy in predicting free-living energy expenditure than the accuracy of the models obtained with the $Tracmor_D$. Carter et al. (22) developed a model to predict TEE using as independent variables body height and activity counts as measured with the 3dNXTM accelerometer (size: 12.5 x 5.8 x 0.8 cm; BioTel Ltd., Bristol, UK). However, the 3dNXTM accelerometer did not show any association with PAL neither with AEE/kg, which are parameters directly related to physical activity. Plasqui et al (24) measured physical activity using an early version of the Tracmor accelerometer (size: 7.2 x 2.6 x 0.7 cm; Philips Research, Eindhoven, The Netherlands) and developed a prediction model of TEE using as independent variables SMR, and activity counts. The explained variation of the model was 90%. Using the $Tracmor_D$, the model based on the same independent variables showed to explain the variation in TEE for 76%. Furthermore, Plasqui et al. (24) developed a model to predict TEE using as independent variables age, body mass, height, and activity counts (Table 4). In our study, TEE was predicted by body mass and Cnts/d. This model explained 54% of the variation in TEE while Cnts/d accounted for 23% to the explained variation in TEE. Although comparing these prediction models is difficult because of the different independent variables included in the regression, it appeared that the ones developed in our study showed a lower explained variance in TEE. However, the contribution of Cnts/d to explain the variation in TEE was similar for the Tracmor and for the $Tracmor_D$ (Table 4).

Table 4. Accuracy of different accelerometers in predicting TEE and AEE compared to doubly-labeled water measures.

Device	Study	Dependent	Independent	r^2	Δr^2 Cnts/d
Actigraph	Masse et al. (26)	TEE	BM, Cnts/d	38 %	5%
Actigraph	Masse et al. (26)	TEE	FFM, Cnts/d	43 %	2%
3DNXTM	Carter et al. (22)	TEE	H, Cnts/d	73 %	27%
Tracmor	Plasqui et al. (24)	TEE	Age, BM, H, Cnts/d	83%	19%
Tracmor_D	This study	TEE	BM, Cnts/d	54%	23%
Actigraph	Assah et al. (27)	AEE/kg	Cnts/d	14 %	14%
Actigraph	Masse et al. (26)	AEE	BM, Cnts/d	9 %	5%
Actigraph	Masse et al. (26)	AEE	FFM, Cnts/d	12 %	4%
Tritrac R3D	Jacobi et al. (28)	AEE	Cnts/d	N.S.	N.S.
Tracmor	Plasqui et al. (24)	AEE	Age, BM, H, Cnts/d	81%	33%
Tracmor_D	This study	AEE	BM, Cnts/d	46%	16%

Dependent, predicted parameter; Independent, parameters used in the prediction equation; r^2, correlation coefficient of the model; Δr^2 Cnts/d, contribution to the correlation coefficient of the accelerometer output; AEE, activity energy expenditure; TEE, total energy expenditure; AEE/kg, AEE corrected by body mass; BM, body mass; FFM, fat free mass; Cnts/d, counts per day which represents the accelerometer output; H, height; N.S., not statistical significance.

Improvements in the prediction accuracy of energy expenditure have been proposed by addressing specific issues related to accelerometer-based measurements of physical activity, such as the non-uniqueness in the relation between activity counts and the intra-individual variability in AEE (14, 29). For example, activities like running and cycling might generate a different amount of activity counts even at similar rates of AEE. For this reason, systems able to identify types of physical activity have been developed to correct for the dissimilar contribution to AEE of different activity types. The Intelligent Device for Energy Expenditure and physical Activity (IDEEA) (MiniSun LLC, Fresno, CA) and the ActiReg (PreMed AS, Oslo, Norway) have been proposed to identify activity type and to determine AEE by considering which category of activity was performed by the subject (15, 30). These activity monitors are relatively complex systems: the IDEEA and the ActiReg are constituted by, respectively, 5 and 2 wire connected acceleration and tilt sensors, to be placed in different locations of the body. This highly reduces the wearability of the monitoring system and it might interfere with the individuals' activity behavior. However, recent advances in accelerometer-based activity monitoring allowed the development of methods to identify types of daily physical activity using a single tri-axial accelerometer, such as sitting, standing, walking, running, and cycling (31), or to distinguish between locomotive and lifestyle activities (12). The IDEEA showed high accuracy for estimating TEE measured using indirect calorimetry during standardized activity trials or during stay in respiration chamber (11, 32).

However, no data is available on the performance of this sophisticated activity monitor in free-living conditions. Conversely, the ActiReg has been validated against DLW, but the accuracy of the model in predicting TEE (r^2 = 64%) was comparable to that observed in studies in which much simpler activity monitors were used to monitor physical activity (15).

A limitation of this study could be identified in the fact that the most accurate TEE prediction model was based on the measured SMR to account for differences in body size. Considering that measuring SMR requires a consistent effort, this accurate prediction model might have limited applicability in large population studies. It should be also noted that even if the contribution of the Tracmor and of the Tracmor_D in predicting energy expenditure was similar, the two instruments are equipped with a different acceleration sensor. Indeed, as the Tracmor is based on the piezoelectric technology, the Tracmor_D is equipped with a capacitive accelerometer, which allows the detection of both dynamic and static accelerations.

In conclusion, this study showed that the Tracmor_D is a highly accurate instrument for predicting free-living energy expenditure. TEE could be explained for 76% when SMR and Cnts/d were included in the prediction model. Although the Tracmor_D is smaller, lighter and less energy consuming than several other activity monitors, the measured Cnts/d significantly contributed to the explained variance in TEE, which was similar to that reported for the Tracmor accelerometer. This means that the improvement in miniaturization did not harm the ability of the Tracmor_D in collecting information of the body acceleration to correctly quantify physical activity for determining TEE, AEE, and PAL.

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Chapter 3

Detection of type, duration and intensity of physical activity using an accelerometer

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Abstract

OBJECTIVE: The aim of this study was to develop models for the detection of type, duration and intensity of human physical activity using one tri-axial accelerometer. METHODS: Twenty subjects (age 29±6 years, BMI 23.6±3.2 kg/m^2) performed 20 selected activities, including walking, running, and cycling, wearing one tri-axial accelerometer mounted on the lower back. Identification of activity type was based on a decision tree. The decision tree evaluated attributes (features) of the acceleration signal. The features were measured in intervals of defined duration (segments). Segment size determined the time resolution of the decision tree to assess activity duration. Decision trees with a time resolution of 0.4, 0.8, 1.6, 3.2, 6.4, and 12.8 seconds were developed and the respective classification performances were evaluated. Multiple-linear regressions were used to estimate speed of walking, running, and cycling based on acceleration features. RESULTS: Maximal accuracy for the classification of activity type (93%) was reached when the segment size of analysis was 6.4 or 12.8 seconds. The smaller the segment size the lower was the classification accuracy achieved. Segments of 6.4 seconds gave the highest time resolution for measuring activity duration without decreasing the classification accuracy. The developed models estimated walking, running and cycling speeds with standard error of 0.20, 1.26 and 1.36 km/h, respectively. CONCLUSION: This study demonstrated the ability of a tri-axial accelerometer in detecting type, duration and intensity of physical activity using models based on acceleration features. Future studies are needed to validate the presented models in free-living conditions.

Introduction

Physical activity (PA) is recommended to improve health and reduce risk for several diseases, such as cardiovascular diseases, diabetes mellitus type II, osteoporosis, obesity, and certain types of cancer (1-4). For this reason, objective assessment of PA in free-living conditions is an important component of many scientific investigations aimed at defining the effectiveness of intervention strategies to increase PA. Furthermore, measuring accurately pattern, duration, and intensity of PA is required to improve the understanding of individuals' behavior and to quantify the relation between PA and diseases outcomes.

A variety of methods exist to objectively measure PA in daily life (5). Ideally, PA should be measured for a period of time representative of the habitual activity level, with minimum discomfort for the subject and using low cost systems for implementation in large-scale studies. Activity monitors based on an accelerometer sensor reasonably satisfy these requirements, and therefore they have been widely used to monitor PA. Accelerometer output, as defined by arbitrary acceleration units per minute (AAU), reflects pattern, duration and intensity of PA and it is used to estimate activity related energy expenditure (6, 7). However, the description of PA by measuring AAU has limitations. AAU has limited ability to identify types of PA performed. This information is important since it may improve assessment of activity pattern and intensity. Furthermore, measuring PA in epochs of one minute limits the time resolution for determining activity duration. Thus, improvements in the assessment of types, duration and intensity of PA are necessary to correctly evaluate habitual PA.

In recent decades, accelerometer sensors have been adopted to identify human movements by using classification algorithms. Zhang et al. (8) proposed a method based on several accelerometers positioned in different body parts (chest, legs, and feet) to identify up to 32 movements and postures achieving a classification accuracy of 95%. In other studies, multiple sensors have been employed to identify several types of PA achieving a classification accuracy from 85% to 95% (9, 10). More recently, identification of PA has been investigated using one single acceleration sensor, placed around the waist (11, 12) or on the chest (13). Then, the overall classification accuracy was between 71% and 91% to identify postures, walking and various sport activities such as rowing, running and cycling. The most common classification algorithms are decision trees (9, 13), neural networks (8), Bayesian classifiers (14) and hidden Markov models (15). These algorithms identify activity types by evaluating attributes of the acceleration signal measured in portions of defined length (segments). A segment of the acceleration includes a certain number of data points determined by the sampling frequency of the signal and by the time length of the segment. Given a certain sampling frequency, the longer the segment size the more samples are considered to calculate attributes (features) of the acceleration. Acceleration features are used to classify the type of activity performed in a certain time interval. The use of short segments for the calculation of the acceleration features would improve the ability to correctly recognize short activities and to measure activity duration, supposing that the classification performances are constant regardless of the segment size.

Detection of activity intensity is essential for measuring PA. According to Ainsworth et al (16), the categorization of dynamic activities such as walking and cycling into light, moderate or vigorous intensity depends largely on movement speed. In the past, accelerometers have been used to assess intensity of PA by measuring AAU. Several studies showed a linear relationship between AAU and activity intensity as defined by energy expenditure measured using indirect calorimetry (17-19). However, this linearity is valid only within one single activity type (19). Additionally, this AAU-based method can only be applied to activities with duration longer than 1 minute. For this reason, improvements are required to evaluate intensity of a variety of activities in daily life. Recently, trunk mounted accelerometers have been used to assess speed of walking. Schutz et al. (20) proposed an algorithm to estimate the walking speed based on features of the acceleration signal. Other studies (21, 22) proposed to measure walking speed estimating gait characteristics such as step length and duration of the stride cycle, by using the acceleration of the body. Nowadays, the most accurate method to measure walking, running and cycling speed in daily life is based on accelerometers and global positioning systems (GPS) (23). However, accurate GPS units have limited wearability and are still too expensive to be used in large-scale studies (24).

The purpose of this study was threefold. The first aim was to use one tri-axial accelerometer to identify a large number of activities like walking, running, cycling, standing, sitting and lying developing a decision tree model. The second aim was to determine the highest time resolution achievable preserving the classification performance of the model. For this purpose a decision tree was developed using features measured in non-overlapping segments of different length and the consequent classification performance was evaluated. The third aim was the definition of intensity for common dynamic activities like walking, running and cycling, investigating the association between features of the acceleration signal and movement speed.

Methods

Subjects

Twenty healthy adults (13 men and 7 women) were recruited by advertisement in local newspapers. All subjects gave written informed consent to participate in the study, which was approved by the Ethics Committee of the Maastricht University Medical Centre. Subjects' characteristics are described in Table 1.

Table 1. Subjects' characteristics.

	All	Calibration	Validation
n (M/F)	20 (13/7)	15 (10/5)	5 (3/2)
Age, y	29 ± 6	29 ± 7	28 ± 5
Weight, kg	72 ± 9.0	70.5 ± 9.9	74.3 ± 5.7
Height, m	1.74 ± 0.09	1.75 ± 0.09	1.74 ± 0.12
BMI, kg/m^2	23.6 ± 3.2	23.1 ± 2.7	24.9 ± 4.6

BMI, body mass index; All, subjects' characteristics of the population used for the development and for the cross-validation of the decision trees. Calibration, subjects' characteristics of the population used for the development of the models to estimate walking, running, and cycling speed; Validation, subjects' characteristics of the population used to test the performance of the models to predict speed.

Instrumentation

Body acceleration was measured with a modified version of "the tri-axial accelerometer for movement registration" (Tracmor, Philips Research, Eindhoven, Netherlands) as applied in previous studies for the assessment of PA (6, 7). Sensor and data logger were integrated in one device. The sensor detected accelerations in three perpendicular directions and the sampling frequency of the signal was set to 20 Hz. The device could record up to 36 hours at this sampling frequency. The device size was 8 x 3.5 x 1 cm and the weight was 34.8 grams (battery included). The device is currently used for research purposes, and it is not commercially available. During the trial the device was attached on the lower back using an elastic belt and it was positioned under the clothes to maximize the comfort for the subject. The device was oriented to have the x, y and z axis sensing acceleration in the vertical, medio-lateral and antero-posterior direction of the body, respectively.

Experimental Methods

The experimental setup consisted of series of physical activities performed in supervised conditions. The subjects were involved in the following activities: lying on a bed, sitting on a chair, sitting while working on a computer, standing, standing washing dishes, walking along a corridor, walking downstairs and walking upstairs, walking outdoors, running outdoors and cycling (Figure 1). The walking and running outdoors activities were conducted on a level and straight sidewalk of 226 m. The cycling part was performed on a straight street of 428 m. The subjects were instructed to perform four walking, running and cycling outdoor tasks adopting four different speeds voluntarily chosen. Average speed was measured by dividing the path length covered by the duration of the activity task. During the cycling activities the same bicycle with a rear wheel size of 0.71 m and a gear ratio of 48/20 was used by the test participants. The starting and finishing time of each activity was recorded with a stopwatch. The Stopwatch and the internal clock of the accelerometer were synchronized to the same reference.

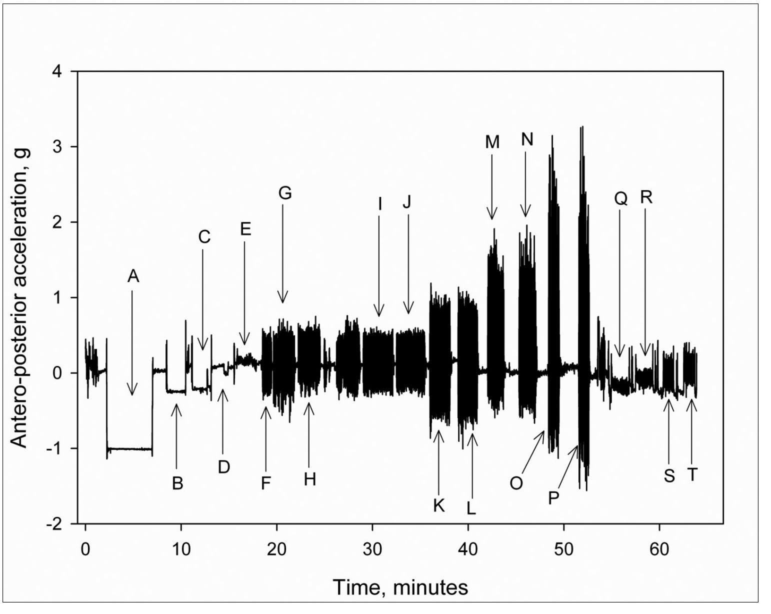

Figure 1. Acceleration measured in the antero-posterior direction of the body (z-axis) during the experimental protocol. Arrows highlight the signal measured during the tasks included in the test: A) lying; B) sitting; C) sitting working on a computer; D) standing; E) washing dishes; F) walking along a corridor; G) walking downstairs; H) walking upstairs; I-L) walking outdoor; M-P) running outdoor; Q-T) cycling outdoor.

Data Processing

The acceleration signal of each activity task was isolated according to the starting and the finishing time as recorded with the stopwatch. Valid data for each activity task was considered from 5 seconds after the starting time to 5 seconds before the finishing time. This 5 seconds time delay was set to analyze only data recorded during a stationary state for each activity, and it was determined by visual inspection of the dataset. The isolated acceleration signal was then processed to calculate features to use for the development of an activity classification model. Accurate assessment of activity duration requires analysis in small segments, but segments of larger size might carry more meaningful information on the type of activity and improve the recognition of PA. To investigate which segment size allowed the highest classification accuracy, six decision tree were developed by analyzing the acceleration signal using segments of 0.4, 0.8, 1.6, 3.2, 6.4 and 12.8 seconds, including 8, 16, 32, 64, 128 and 256 samples, respectively. The acceleration signal stored in each segment was processed to extract features in the time and frequency domain.

The acceleration features in the time domain were: the average ($\bar{a}$), the standard deviation (σ), the peak-to-peak distance (a^{pp}), the cross-correlation (R) of the acceleration in the same axis and the R of the acceleration between sensing axes. The R of the acceleration between axes was calculated as presented in Equation 1 and 2.

$$R_{\alpha\beta} = \max\left(r_{\alpha\beta}\right) \qquad \text{[\textit{Equation 1}]}$$

$$r_{\alpha\beta}(i) = \begin{cases} \sum_{j=0}^{N-i-1} \alpha_{i+j}\, \beta_j, & i \geq 0 \\ r_{\alpha\beta}(-i), & i < 0 \end{cases} \qquad \text{[\textit{Equation 2}]}$$

Where α and β represent two subsequent segments of the same axis, *i* is the shift between the two segments and *j* is an index that covers the full length of the overlapping samples between α and β. *N* represents the segment size. This feature provided a measure of the similarity in the acceleration over two subsequent time intervals for the same axis. The *R* of the acceleration between axes was also calculated as defined in Equation 1 and 2. In this case, α and β represent segments of the acceleration in the same time interval but recorded on different axes. This feature provided a measure of the similarity in the acceleration between axes. Some features were also computed in the frequency domain. Firstly, the power spectral density (*P*) of the acceleration was used to define the harmonic content of the signal. *P* was calculated using the fast Fourier transform algorithm on the acceleration signal of each segment. After that, attributes of *P* were described by frequency domain features, such as the dominant frequency, the amplitude of the spectral peak (*A*), and the frequency domain entropy (*J*). The dominant frequency was the frequency at which *P* had the maximum value. The *A* was defined as the maximum value of *P*, and *J* was defined as in Equation 3.

$$J = -\sum_{i=1}^{N/2} \left[\bar{P}(i) \cdot \log\left(\bar{P}(i)\right)\right] \qquad \text{[\textit{Equation 3}]}$$

Where $\bar{P}$ is the normalized power spectral density, *i* is an index that cover the entire length of *P*, and *N* is the number of samples contained in the segment of the acceleration. These features were measured for each axis and used for the classification of the segments. The processing scripts used to calculate the features were developed using Matlab (The MathWorks, Natick MA).

Modelling and statistics

Decision trees models were developed to identify activity types, as proposed earlier (9, 13). The activity tasks performed by each subject during the experimental protocol were grouped in categories addressed by the decision tree. These categories were: “lie”, “sit”, “stand”, “dynamic standing” (DS), “walk”, “run”, and “cycle”. The lying task was labeled as “lie”, the sitting and working on a computer tasks were labeled as “sit” and the standing task was labeled as “stand”. The washing dishes task, dynamic standing, was labeled as “DS”. The walking along a corridor, walking downstairs, walking upstairs and walking outdoor tasks were labeled as “walk”. The running and cycling tasks were labeled as “run” and “cycle”, respectively.

The development of the decision tree consisted of two main steps. The first step was the selection of the best features to use for the classification of the training dataset. The second step was the definition of logical conditions based on the selected features to drive the classification of the training dataset. For each segment size used to calculate acceleration features, a decision tree was developed. The classification performance of each decision tree was tested using the leave-one-subject-out cross-validation algorithm (25). The classification accuracy and F-score obtained from the cross-validation was used to determine which segment size allowed the development of the decision tree with the highest classification performance. The classification accuracy was defined as the average percentage of correctly classified segments over the entire set of cross-validation segments as measured at each step of the leave-one-subject-out cross-validation. The F-score was calculated as the average of the harmonic mean between sensitivity and positive predictive value measured at each step of the leave-one-subject-out cross-validation (Equation 4). This parameter was defined to evaluate the overall performance of the model specifically for each activity type.

$$\text{F-score}_k = \frac{1}{20}\sum_{i=1}^{20} 2\frac{Se_k \cdot PPV_k}{Se_k + PPV_k} \qquad [\textit{Equation 4}]$$

where *i* is an index that represents each step of the leave-one-subject-out cross-validation, *k* represents the type of activity considered, the constant 20 is the number of steps in the leave-one-subject-out cross-validation, *Se* is the sensitivity of the decision tree for the *k*-activity type, and PPV is the positive predictive value of the decision tree for the *k*-activity type. *Se* describes the ability to avoid false negative classifications for a certain activity type. PPV defines the ability to avoid false positive classifications for a certain activity type. Considering the number of true positive classification (TP), false positive classification (FP), true negative classification (TN), and false negative classification (FN), *Se* was calculated as TP/(TP+FN), and PPV as TP/(TP+FP). The Student t-test was used to determine differences in the classification accuracy of the decision trees trained using different segment length. The classification accuracies were expressed as average ± standard deviation. Statistical significance level was set to $P<0.05$. The development of the classification models and the cross-validation was performed using Matlab (The MathWorks, Natick MA). The C4.5 algorithm (26) was used for the training and pruning of the decision tree. The minimum number of objects included in the terminal branches of the decision tree was set to 5% of the training instances.

Three separate models were developed to estimate walking, running and cycling speed for the outdoors tasks. Stepwise multiple-linear regression was used to select the best independent elements to include in the models. The independent elements of the models were body characteristics and acceleration features measured in segments of 6.4 sec and averaged over the entire duration of the activity task. The study population was divided in two groups: the "calibration group" (75 %) and the "validation group" (25 %). Subjects were randomly assigned to the calibration or the validation group. Data from the calibration group was used to develop the models to estimate walking, running and cycling speed. Data from the validation group was used to test the performance of the developed models. The standard error of estimation (SEE) was defined to measure the ability of the developed models in fitting the measured speed of the calibration population. The standard error of validation (SEV) was defined to determine the ability of the models in predicting the measured speed of the validation population. Furthermore, the residuals between estimated and measured speeds of the validation population were analyzed to define the bias and the limits of agreement of the models with the measurements (27). The development of these models to estimate speed and the statistical analysis of the prediction performance was conducted using Matlab statistical toolbox (The MathWorks, Natick MA) and SigmaStat (Systat software, San Jose CA).

Results

Activity classification

The Subjects' characteristics of the study population are presented in Table 1. Decision trees developed using segments of 12.8 seconds and 6.4 seconds showed the highest classification accuracy. The smaller the segments size considered the lower was the classification accuracy (Table 2). There was no significant difference between the classification accuracy of the models developed using segments of 12.8 and 6.4 seconds ($P = 0.41$). The paired t-test between the classification accuracy of the models developed using segments of 3.2 and 1.6 seconds showed a $P = 0.05$. The paired t-test between the classification accuracy of all the other models showed a statistically significant difference ($P<0.05$). The F-scores of the decision tree developed using segments of 12.8 seconds for each activity types ranged from 60 % to 100 % (Table 2). The features selected to classify activity types were stable at each step of the cross-validation and were also stable for each segment length considered (Figure 2).

Table 2. Classification performances of the decision trees developed using different segment sizes.

Segment size, seconds	Classification accuracy, %	F-score, %						
		Lie	Sit	Stand	DS	Walk	Run	Cycle
0.4	90.4 ± 0.3	**100.0**	85.7	53.9	67.6	97.3	99.1	89.3
0.8	91.9 ± 0.2	**100.0**	86.4	59.6	71.9	98.3	99.7	92.2
1.6	92.3 ± 0.3	**100.0**	86.6	58.0	72.8	98.8	99.9	93.3
3.2	92.6 ± 0.3	**100.0**	86.7	59.7	72.5	99.1	**100.0**	93.4
6.4	93.1 ± 0.5	**100.0**	**87.4**	**62.4**	**75.2**	99.2	**100.0**	93.9
12.8	93.0 ± 0.6	**100.0**	86.4	60.0	74.5	**99.5**	**100.0**	**95.1**

Segment size, length of the intervals used to segment the acceleration; Classification accuracy, percentage of the correctly classified segments over the entire set of cross-validation segments; F-score, harmonic mean of sensitivity and specificity of the classification method; DS, dynamic standing; bold numbers are the maximum value of F-scores.

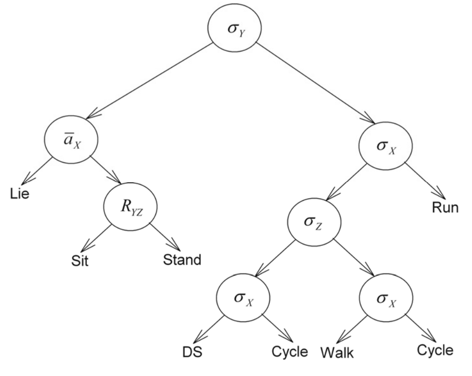

Figure 2. Structure of the decision tree developed using segments of 6.4 seconds. The circles represent decision nodes. In the decision nodes logic conditions based on the noted features distinguish the 7 activity types (lie, sit, stand, dynamic standing (DS), walk, run, cycle). The features selected for the classification were: the standard deviation of the acceleration in the vertical, medio-lateral, and antero-posterior direction (σ_X, σ_Y, σ_Z); the average acceleration in the vertical direction of the body ($\bar{a}_X$) ; and the cross-correlation of subsequent intervals of the acceleration in the antero-posterior direction (R_Z).

Speed estimation

Subjects' characteristic for the calibration and the validation group were similar (Table 1). Measured walking, running and cycling speeds were 5.2 (±0.9) km·h^{-1}, 9.8 (± 2.2) km·h^{-1}, and 16.0 (± 4.0) km·h^{-1}, respectively. The model to estimate walking speed showed a SEE of 0.2 km·h^{-1} and a SEV of 0.47 km·h^{-1}. The model had a bias of 0.32 km·h^{-1} with ± 95% prediction limits ± 0.70 km·h^{-1} (CI: – 0.38 to 1.02 km·h^{-1}). The model to estimate running speed showed a SEE of 1.26 km·h^{-1}. The SEV was 2.45 km·h^{-1}. This model overestimated the measured speed with a bias of 0.29 km·h^{-1} with ± 95% prediction limits ± 4.89 km·h^{-1} (CI: – 4.6 to 5.18 km·h^{-1}). The model to estimate cycling speed showed a SEE of 1.36 km·h^{-1}. The

SEV was 2.88 km·h^{-1}. This model had a bias of 0.26 km·h^{-1} with ± 95% prediction limits of ± 5.76 km·h^{-1} (CI: – 5.50 to 6.02 km·h^{-1}). The independent elements of the three models are presented in Table 3.

Table 3. Models to estimate walking, running and cycling speed.

Walking speed (r^2 = 96.3%)				
Var.	Coef.	SE	Part-r^2	P
Int.	55.18	13.06		
$\ln(\sigma_X)$	2.29	0.08	84.5	<0.001
R_{XY}	$2.65 \cdot 10^{-8}$	$0.24 \cdot 10^{-8}$	89.5	<0.001
H	2.42	0.30	93.8	<0.001
$\bar{a}_X$	- 0.03	0.0057	95.2	<0.001
J_X	- 0.13	0.03	96.3	<0.001
Running speed (r^2 = 70.2%)				
Var.	Coef.	SE	Part-r^2	P
Int.	- 53.76			
$a^{pp}{}_z$	0.006	$9.39 \cdot 10^{-4}$	53.5	<0.001
R_{ZX}	$8.88 \cdot 10^{-8}$	$1.68 \cdot 10^{-8}$	64.1	<0.001
A_Z	$-7.81 \cdot 10^{-6}$	$3.33 \cdot 10^{-6}$	67.3	0.023
A_Y	$5.36 \cdot 10^{-6}$	$1.97 \cdot 10^{-6}$	70.2	0.009
Cycling speed (r^2 = 86.6%)				
Var.	Coef.	SE	Part-r^2	P
Int.	4.76			
σ_Z	0.33	0.03	78.7	<0.001
f_Z	1.01	0.26	85.0	<0.001
σ_X	0.06	0.02	86.6	0.012

r^2, correlation coefficient; Var, acceleration features selected as predictors; Coef, coefficients of the variables; SE, standard error; Part-r^2, partial r^2; P, statistical significance level. Int, intercept; $\ln(\sigma_X)$, ln of the standard deviation (x axis); R_{YZ}, cross-correlation between the acceleration measured in the medio-lateral and antero-posterior directions (y and z axis); H, body height; $\bar{a}_X$, average acceleration (x axis); J_X, frequency-domain entropy (x axis); $a^{pp}{}_Z$, peak-to-peak distance (z axis); R_{ZX}, cross-correlation between the acceleration measured in the antero-posterior and vertical directions (z and x axis);A_Z, A_Y, amplitude of the power spectral density peak (z axis, and y axis);σ_Z, σ_X, standard deviation (z axis, and x axis); f_Z, dominant frequency of the power spectral density (z axis).

Discussion

Classification of physical activity

In this study we developed a method to identify types of PA. The classification process was based on information carried by features of the acceleration of the body as measured using one single tri-axial accelerometer placed on the lower back. Based on this information, a decision tree showed high accuracy in identifying activity types. Measuring acceleration features in intervals of 6.4 or 12.8 seconds the highest classification accuracy (93%) was achieved.

During the experimental protocol 20 standardized activities were performed by the subjects. These activities were grouped in 7 classes which represent common types of daily PA. The lying, sitting, and standing classes were defined to represent human postures. The walking and running classes were defined to represent gait and ambulation. The dynamic standing class was defined to represent human movements performed in the standing position not related to ambulation. Additionally, the cycling class was considered since cycling is a popular means of transport for trips of short distance in several countries (28).

A close examination of the structure of the decision tree developed using segments of 6.4 seconds permitted to understand the role of the different features in the classification process (Figure 2). The standard deviation of the acceleration in the medio-lateral direction (σ_Y) was the feature used to group in one branch activities as "lie", "sit", and "stand" and to group in the other branch activities as "DS", "walk", "run", "cycle". Thus, the standard deviation of the acceleration in this direction of the body acquired high value for dynamic or ambulatory movements while it attained low values for static activities. The orientation of the vertical direction of the body with respect to the direction of gravity ($\bar{a}_X$) was the feature used to identify lying. The cross-correlation between subsequent time intervals of the antero-posterior acceleration (R_Z) was used to identify sitting and standing. A high value of the standard deviation (σ_X) of the acceleration in the vertical direction of the body was characteristic of running. Classification of the "walk", "cycle" and "DS" types was mainly determined by the standard deviation (σ_Z, σ_X) in the antero-posterior and vertical direction of the body. The decision tree showed high performance for identifying lying, sitting, walking, running and cycling, since the F-score associated to these activities was above 86 % in the models based on segments of 6.4 and 12.8 seconds. Thus, appropriate acceleration features were considered to classify these activities. Standing and dynamic standing were frequently misclassified by the decision tree and this was reflected by the relatively low F-score. The reason was that washing dishes was a standing activity characterized by acceleration of small magnitude, and therefore there were not features able to clearly discriminate the acceleration of these two activities.

The identification of lying, walking, running, and cycling, using the decision tree developed with segments of 6.4 seconds, showed an accuracy comparable to that obtained in other studies where PA was measured using several sensors positioned in different body parts (Table 4). However, the use of one accelerometer presented a limited ability to identify the sitting and standing postures. The decision trees trained using segments of 6.4 and 12.8 seconds showed an elevated classification accuracy as compared to the one obtained in earlier studies (11, 13, 15). However, it is worth to notice that in the current study the acceleration signal of each activity type had different duration. According to the test protocol, a greater number of walking, running, and cycling segments were collected as compared to the number of sitting, standing and DS segments. In view of the fact that walking, running, and cycling were identified more easily by the decision tree than sitting, standing and DS, the disproportion in the number of segments per activity type determined a general increase of the classification accuracy. Furthermore, the fact that the DS class was represented by one activity task in the experimental protocol could be recognized as a limitation of this study, since there is a broad range of household and lifestyle related activities that might be considered to define this category.

Table 4. Classification performance of different models to identify types of physical activity.

	Sensors	Lie, %	Sit, %	Stand, %	Walk, %	Run, %	Cycle, %
Zhang et al. (29)	5	99	99	99	99	99	N.C.
Bao et al. (2)	5	95	95	96	90	88	96
Foerster et al. (10)	4	89	100	88	99	N.C.	100
Ermes et al. (8)	2	99	N.C.*	N.C.*	81	90	91
Karantonis et al. (15)	1	74	N.C.	N.C.	90	N.C.	N.C.
Mathie et al. (21)	1	99	N.C.*	N.C.*	100	N.C.	N.C.
Current study	1	100	85	59	99	100	96

Sensors, number of sensors employed to measure acceleration; % values, represents sensitivity of the model developed to identify activity types; Current study, sensitivity data relative to the decision tree developed using segments of 6.4 seconds; N.C., not considered; *, sitting and standing were defined as a single activity class, and the classification accuracy was of 95%.

Assessment of activity duration

The accurate assessment of activity duration is important for the correct evaluation of individuals' behavior. In free-living conditions many activities are discontinuous and have a short duration, for instance the daily walking activity comprises many short bouts as pointed out in a recent investigation by Levine et al (29). The assessment of activity duration requires the correct detection of the instants at which an activity starts and finishes. The approach adopted by decision trees for the identification of activity type, which is based on segment by segment analysis, encumbers the exact detection of the activity boundaries. In natural conditions the segmentation would rarely match with the beginning or the end of an activity. Therefore, the performances of the classification model at the boundaries of an activity are unpredictable since the segment will present partly the features of the previous or of the following activity and partly the features of the activity under investigation. This boundary ambiguity of the acceleration features might generate a misclassification and consequently the activity duration can be incorrectly estimated. Additionally, activities of duration smaller than the segment size may be misclassified as the information contained in the measured features will not only belong to the considered activity but also to the adjacent parts. However, these errors are minimized if the segment has a short length. Thus, the advantages offered by the use of short intervals for the segmentation of the acceleration signal is the reduced error in the definition of activity duration and the increased accuracy in the classification of short activities. When the segmentation of the acceleration signal is made by considering contiguous intervals, the use of short intervals would increase the time resolution of analysis, which improves the detection of activity duration. Another method employed to increase the time resolution is the segmentation of the signal in overlapping intervals for the calculation of acceleration features. Using this technique, the time resolution is determined by the level of overlap between segments, and it can be increased without reducing the segment size. However, because of the overlap, misclassifications due to activity transitions would affect more segments. Thus, the shorter are the segments of analysis the lower would be the propagation of the classification error due to activity transitions, improving in this way the definition of activity duration.

In this study we reported that the use of short intervals for the computation of acceleration features led to a reduction of the classification accuracy. Using features measured in segments of 0.4 seconds reduced by 3% the classification accuracy as compared to the one obtained with segments of 6.4 and 12.8 seconds. The decline of classification performance for small segments of analysis concerned most of the activity types as shown by the decrease of the F-score. This can be explained by the fact that the features had a higher intra-class variability (variability within the same activity class) when computed in shorter segments. Given that decision trees discriminate features belonging to different activities by defining cut-off values, in case the features have higher intra-class variability the risk of overlapping between values of different activities is higher. This reduces the ability of the cut-off values to distinguish activity types, which results in a decrease in the classification accuracy of the decision tree. However, the accuracy to identify PA was similar for the model with time resolution of 6.4 seconds as compared to the model with time resolution of 12.8 seconds. Thus, segmenting the acceleration signal in non-overlapping windows of 6.4 seconds gave the highest time resolution for measuring activity duration without decreasing the classification accuracy.

Estimation of activity intensity

Intensity of walking, running and cycling is largely determined by speed. According to Ainsworth et al. (16) movement speed could be used to categorize walking, running and cycling in intensity levels, such as light (Metabolic equivalent [MET] < 3), moderate (3 < MET < 6) or vigorous (MET > 6). For example, walking below 4 km·h^{-1} could be defined as light intensity activity. Walking between 4 and 7.2 km·h^{-1} can be defined as moderate intensity activity, and walking above 7.2 km·h^{-1} could be defined as vigorous intensity activity (16). Furthermore, a linear association was observed between walking, running and cycling speed and energy expenditure. The slope of the linear regression describing these relationships was estimated to be of 0.8 MET·km^{-1}·h, 0.77 MET·km^{-1}·h, and 0.66 MET·km^{-1}·h, for walking between 3 and 5 km·h^{-1}, for running, and for cycling respectively (16, 30). In this study, acceleration features and body characteristics were used to develop models to estimate walking, running and cycling speed. The employment of these models in intervals of the acceleration identified as walking, running, or cycling allows the evaluation of activity intensity specific for the type of PA. This approach seems to be in line with the method proposed by Crouter et al (31) to improve the prediction accuracy of energy expenditure using accelerometer output. Compared to GPS estimates, the proposed models had lower accuracy. However, the SEE of the walking speed model was still similar to the one achieved in models based on GPS measurements (23).

The applicability in a natural condition of the cycling speed estimation might present limitations. The reason was that during the experimental protocol only one bicycle and one specific gear was used by the subjects. Therefore, the performance of the model should be tested on different bicycles to confirm the validity of the estimation properties. Furthermore, the limitation of this method for the assessment of activity intensity was that the effect of walking, running or cycling on slopes was not considered. Hence, the intensity of moving uphill or downhill might be incorrectly evaluated.

Conclusion

This study demonstrated the ability of a tri-axial accelerometer in detecting type, duration and intensity of physical activity by using models based on acceleration features. Future studies are needed to validate the presented models in free-living conditions and in specific populations like children, elderly and obese subjects.

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Chapter 4

Improving the assessment of daily energy expenditure by identifying types of physical activity using a single accelerometer

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Abstract

BACKGROUND: Accelerometers are often used to quantify the acceleration of the body in arbitrary units (counts) to measure physical activity (PA) and to estimate energy expenditure. OBJECTIVE: The present study investigated whether the identification of types of PA using one accelerometer could improve the estimation of energy expenditure as compared to activity counts. METHODS: Total energy expenditure (TEE) of 15 subjects was measured using doubly-labeled water. The physical activity level (PAL) was derived dividing TEE by sleeping metabolic rate. Simultaneously, PA was measured using one accelerometer. Accelerometer output was processed to calculate activity counts per day (AC_D) and to determine the daily duration of 6 types of common activities identified using a classification tree model. A daily metabolic value (MET_D) was calculated as mean of the MET compendium value of each activity type weighed by the daily duration. RESULTS: TEE was predicted by AC_D and body weight and by AC_D and fat free mass with a standard error of estimate (SEE) of 1.47 $MJ{\cdot}d^{-1}$, and 1.2 $MJ{\cdot}d^{-1}$, respectively. The replacement in these models of AC_D with MET_D increased the explained variation in TEE by 9%, decreasing SEE by 0.14 $MJ{\cdot}d^{-1}$, and 0.18 $MJ{\cdot}d^{-1}$, respectively. The correlation between PAL and MET_D (R^2=51%) was higher than PAL and AC_D (R^2=46%). CONCLUSION: Identification of activity types combined with MET intensity values improves the assessment of energy expenditure as compared to activity counts. Future studies could develop models to objectively assess activity type and intensity to further increase accuracy of the energy expenditure estimation.

Introduction

In many metabolic disorders there is a need to measure daily energy expenditure. The main determinants of energy expenditure are body size and physical activity (PA) (1). Although body size can be easily determined, the assessment of PA represents a challenge, because of the diversified individuals' behaviors and because of the complex nature of human activities. Several methods have been proposed to objectively measure PA (2). Ideally, PA should be measured in free-living conditions, over a period of time representative for the habitual activity level, and with minimal discomfort to the subject. Accelerometers reasonably satisfy these requirements and, therefore, have been widely used for the assessment of PA (2, 3). Traditionally, accelerometer output has been expressed as activity counts to quantify PA. This measure of the acceleration of the body is commonly defined as the area under the rectified acceleration signal measured over a fixed time interval like one minute (4). Activity counts have been used to describe the pattern of PA, i.e. the frequency, the duration and intensity of PA. Furthermore, activity counts proved to be linearly related to the total energy expenditure (TEE), to the activity-related energy expenditure (AEE), and to the physical activity level (PAL) as measured using doubly-labeled water (5-7). TEE is defined as the daily metabolic rate, while AEE corresponds to the portion of TEE consumed for PA. PAL is also commonly used to describe the amount of energy consumed for PA as a fraction of the energy required to maintain basal metabolic functions. Linear models have been developed to predict TEE and AEE using activity counts and subject characteristics such as body weight as independent variables (5, 8). On the contrary, when indirect calorimetry was used to assess the metabolic rate during specific activities, the relationship between the intra-individual variability in AEE and activity counts varied according to the type of activity (9). Similar to TEE and AEE, PAL has been repeatedly predicted by linear models based on activity counts. However, as shown for AEE, the relationship between PAL and activity counts depends on the type of activity (9). Thus, prediction models that account for the type of activity performed could result in more accurate estimates of TEE, AEE and PAL.

In recent years, accelerometers have been used in combination with classification models to identify types of PA by evaluating information (features) derived from the acceleration of the body (10-14). Classification trees (11), neural networks (14), and hidden Markov models (12), are some of the existing classification models used to identify activity type. Zhang et al. (14) developed a neural network to identify up to 32 human movements recording the acceleration of the body using 5 accelerometers. In more recent studies, the identification of activity types was based on the acceleration features measured using a single accelerometer (11, 15). However, the simplification of the measurement system, using one accelerometer, implied a decrease in the number of activities that could be accurately identified by the classification model.

In this study PA was measured during daily life in a population of healthy adults using a single accelerometer. Simultaneously, TEE was assessed using the gold standard technique of doubly-labeled water. The aim was to investigate whether the identification of activity type combined with a simple methodology to define activity type intensity could improve the estimation of TEE, AEE, and PAL as compared to daily activity counts.

Methods

Subjects

Fifteen healthy non-smoking adults (9 men and 6 women) were recruited by advertisement in local newspapers to participate in the study (Table 1). The study was approved by the Ethics Committee of the Maastricht University Medical Center, and written informed consent was obtained from the participants.

Table 1. Subjects characteristics (n = 15).

Parameter	Mean ± SD	Range
n (men/women)	15 (9/6)	
Age, y	41 ± 11	26 – 59
BM, kg	76.6 ± 11.4	62.1 – 103.4
Height, m	1.77 ± 0.08	1.66 – 1.89
BMI, $kg{\cdot}m^{-2}$	24.4 ± 3.0	19.6 – 29.5
FM, kg	20.2 ± 6.1	8.4 – 33.2
FFM, kg	56.4 ± 7.6	44.1 – 70.2
SMR, $MJ{\cdot}d^{-1}$	7.1 ± 0.8	5.7 – 8.3
TEE, $MJ{\cdot}d^{-1}$	12.5 ± 1.9	9.7 – 15.5
AEE, $MJ{\cdot}d^{-1}$	4.1 ± 1.2	2.1 – 6.4
PAL	1.75 ± 0.17	1.43 – 2.06
AC_D, $kcounts{\cdot}d^{-1}$	228 ± 60	116 – 341
MET_D	1.72 ± 0.14	1.48 – 1.98

BM, body mass; BMI, body mass index; FM, fat mass; FFM, fat free mass; SMR, sleeping metabolic rate; TEE, total daily energy expenditure; AEE, activity energy expenditure; PAL, physical activity level; AC_D, daily activity counts; MET_D, daily metabolic equivalent.

Study design

Subjects reported to the laboratory on day 0 at 09h00 p.m. for an overnight stay in a respiration chamber. The study included a two weeks observation period for the measurements of energy expenditure, from the morning of day 1 until the morning of day 15. The PA was monitored from the morning of day 1 until the morning of day 6.

Anthropometrics

Anthropometric measurements were taken in the morning after an overnight fast. Body mass (BM) was measured on an electronic scale (Mettler Toledo ID1 Plus, Giessen, Germany) to the nearest 0.01 kg. Height was measured to the nearest 0.1 cm (SECA Mod.220, Hamburg, Germany). Body volume was determined by underwater weighting. During the underwater weighting the residual lung volume was measured using the helium dilution technique (Volugraph 2000, Mijnhardt, Bunnik, The Netherlands). TBW was determined using deuterium dilution, according to the Maastricht protocol (16). Body composition was calculated from body mass, body volume and total body water (TBW) using the Siri's three-compartment model (17).

Sleeping metabolic rate

Sleeping metabolic rate (SMR) was measured during an overnight stay in the respiration chamber. The room measured 14 m^3 and was equipped with bed, table, chair, freeze toilet, washing bowl, radio, television, and a computer (18). Energy expenditure was calculated from O_2-consumption and CO_2-production according to Weir's formula (19). SMR was defined as the lowest observed energy expenditure for three consecutive hours during the night. Room temperature was held constant at 20 ± 1 °C.

Energy expenditure

The TEE was measured using doubly-labeled water according to the Maastricht protocol (16). On the evening of day 0, after the collection of a background urine sample, subjects drank a weighted amount of $^2H_2{}^{18}O$ such that baseline levels were increased with 100 ppm for ^2H and 200 ppm for ^{18}O. Additionally, urine samples were collected in the morning (from second voiding) of day 1, day 8, and day 15, and in the evening of day 1, day 7, and day 14. The activity energy expenditure (AEE) was measured as (0.9 x TEE) – SMR, assuming the diet-induced thermogenesis to be 10% of TEE. The mean PAL was calculated as TEE/SMR (8).

Physical activity monitoring

The motion sensor used was a modified version of the previously validated Tracmor (Philips Research, Eindhoven, The Netherlands) (4, 8). The device was equipped with a tri-axial capacitive (micro-electro-mechanical system [MEMS]) acceleration sensor and recorded acceleration samples 20 times per second. The accelerometer measured 8 x 3.5 x 1 cm and weighed 34.8 g, including the battery, and was placed at the lower back using an elastic belt. The x-, y-, and z-axes of the accelerometer were oriented along the vertical, medio-lateral and antero-posterior directions of the body, respectively. PA was monitored for 5 consecutive days (2 weekend days and 3 weekdays). Subjects were instructed to wear the accelerometer during waking hours, except during showering and water activities. A diary was used to report periods in which the subject was not wearing the accelerometer during the day.

The raw acceleration signal was downloaded to a personal computer and processed for two purposes. Firstly, to determine the number of activity counts scored daily. The total activity counts accumulated during the monitoring period was divided by the number of days to determine the average activity counts per day (AC_D). Secondly, the raw acceleration signal was processed to identify types of PA performed during the day. The acceleration signal was segmented in non-overlapping intervals of 6.4 seconds. This segment length was selected because the accuracy of classification models used to identify activity types could decrease when the acceleration signal is analyzed in portion of shorter time length (10). In each segment of the acceleration and for each sensing axis, the following acceleration features were determined: average, standard deviation, peak-to-peak distance, and dominant frequency in the power spectral density. Because of the high accuracy in identifying activity types (10, 11), a classification tree algorithm was employed to evaluate the features and to classify the acceleration in one of 6 activity classes: “lie”, sitting or standing (“Sit-Stand”), active standing (“AS”), “walk”, “run” and “cycle”. The AS class was defined to represent dynamic activities not related to ambulation performed in the standing position. The outcome of the classification tree allowed the definition of the duration of the 6 activity types during the monitoring period. The average daily duration (AD_D) of each activity type was calculated as the total duration of each activity divided by the number of monitoring days. The AD_D of lying was determined by integrating the sleeping time, as reported with the diary, to the time spent lying during waking hours.

The AD_D of the identified activity types was used for the assessment of PA by defining a daily metabolic equivalent value (MET_D). The MET_D was calculated as the mean of the standard metabolic equivalent value (MET) of each activity type weighed by the AD_D, as shown in the equation below:

$$MET_D = \frac{1}{k}\sum_{i=1}^{6} MET^i \times AD_D^i$$

where *i* is an index that corresponds to each of the 6 activity types considered; MET^i is the standard MET value for the *i*-activity; AD_D^i is the average daily duration for the *i*-activity (minutes·d^{-1}); and *k* represents the number of monitoring minutes during the day. According to the diaries, the non-wearing time during waking hours was removed from the dataset. This operation was analogue to consider the MET_D of the non-wearing time equal to the average MET_D of the wearing time. The standard MET for each activity type was obtained from a published compendium of PA (20). Since the MET of walking, running, and cycling depends on movement speed, the speed of these activities was estimated by employing recently developed prediction models based on acceleration features (10). The speed of each walking, running, and cycling bout was measured and averaged over the monitoring period and over each subject to have an indication of which MET value would be more suitable to describe the average intensity of the walking, running, and cycling activities.

Classification tree

A classification tree is a model in which the classification process is defined by a sequence of logical conditions based on the features of the object to classify. The development of a classification tree comprises the selection of the features that are most useful for the classification, and the definition of logical conditions to steer the classification. The classification tree employed in the current investigation was developed using data collected during a supervised test, conducted in a separate study with a population characterized by a broad range of weight, height and age: 20 men and 20 women, (mean ± s.d. [min.–max.]) weight = 82 ± 23 [48 - 182] kg, height = 1.71 ± 0.09 [1.49 – 1.97] m, age = 41 ± 16 [23 - 70] y, and BMI = 28.1 ± 7.1 [18.6 – 53.9] kg·m^{-2}. The supervised test included activities such as lying, sitting, standing still, walking, running, cycling, washing dishes and sweeping the floor. The acceleration collected during the dishwashing and floor-sweeping activities were used to define the AS category. The acceleration collected during sitting and standing still was used to define the Sit-Stand category. These two activities have been grouped together to form a single category because the use of one accelerometer to measure PA did not allow the accurate distinction of the sitting and standing still postures (10). Figure 1 shows the structure of the developed classification tree and the features selected for the identification of activity type. Table 2 shows the performances of the classification tree as tested on 5 subjects not included in the population used to develop the model (21). The development of the classification tree was conducted using Weka machine learning toolkit (University of Waikato, Hamilton, New Zealand) (22). The processing scripts used for the features calculation and for the validation of the decision tree were developed using Matlab (The MathWorks, Natick, MA).

Table 2. Performance of the model used to identify types of physical activity

		Classification categories					
		Lie	Sit-stand	AS	Walk	Run	Cycle
True categories	Lie	**100**	0	0	0	0	0
	Sit-stand	2	**95**	3	0	0	0
	AS	0	22	**69**	3	0	6
	Walk	0	0	0	**99**	0	1
	Run	0	0	0	0	**100**	0
	Cycle	0	1	5	7	0	**87**
Sensitivity, %		100	95	69	99	100	87
Specificity, %		99	98	98	98	100	99
F-score, %		100	96	81	99	100	93

Percentage of objects belonging to the true category classified as each classification category; Sensitivity describes the ability to avoid false negative classifications; Specificity defines the ability to generate true positive classifications; F-score is the harmonic mean between sensitivity and positive predictive values and evaluates the overall classification performance of the model (21); AS, active standing; Sit-Stand, sitting or standing.

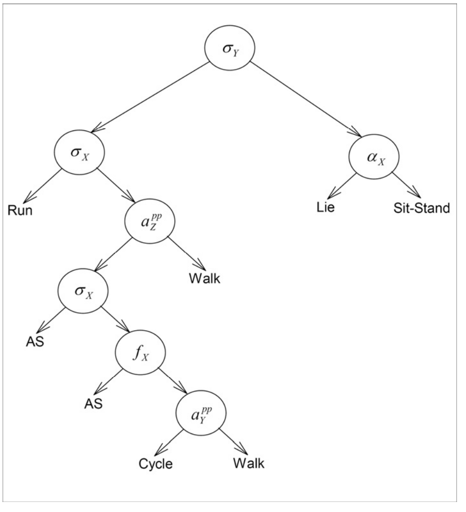

Figure 1. Classification tree developed to identify physical activity types (lie, sit or stand [Sit-stand], active standing [AS], walk, run, cycle). The features selected for the classification were: the standard deviation of the acceleration in the vertical, and medio-lateral directions of the body (σ_X, σ_Y); the average acceleration in the vertical direction of the body (α_X); the peak-to-peak distance of the acceleration measured in the medio-lateral, and antero-posterior direction of the body (a_Y^{pp}, a_Z^{pp}); and the frequency peak of the power spectral density of the acceleration measured in the vertical direction of the body (f_X).

Statistical analysis

Simple linear regression was used to develop prediction models for PAL using as independent variable AC_D or MET_D. The Bland-Altman plot was used to determine the agreement between measured and predicted PAL (23). Stepwise multiple-linear regression analysis was used to select the best independent variables to predict TEE and AEE. Three different sets of independent variables were considered to account for the differences in body size: SMR, basic body characteristics (BM, height, age, and gender) and advanced body characteristics (fat mass, fat free mass [FFM], age, gender). The independent variable used to describe differences in PA was AC_D or MET_D. The independent variables considered in the regression analysis of AEE were the same as in the regression analysis of TEE with the exception of SMR. The correlation between two variables was evaluated by measuring the Pearson's correlation coefficient (r). The measured parameters are presented as mean ± standard deviation. The statistical software SigmaStat (Systat software, San Jose, CA) was used for statistical analysis. The significance level was set to $P<0.05$.

Results

Descriptive results

Physical characteristics of the subjects are presented in Table 1. Subjects wore the accelerometer on average 15.7 ± 0.4 $h \cdot d^{-1}$, which was 93 ± 5% of their waking hours. Sedentary activities like lying, sitting and standing occupied on average more than 75% of the day (Table 3). The average walking, running and cycling speed of the population was 4.2 ± 0.4 $km \cdot h^{-1}$, 10.6 ± 7.1 $km \cdot h^{-1}$, and 20.3 ± 6.0 $km \cdot h^{-1}$, respectively. The MET values selected for each activity type are presented in Table 3. According to a published compendium of physical activities (20), the intensity of lying was considered equal to the MET value of lying quietly. The intensity of sitting or standing was considered equal to the average MET value of sitting quietly, standing quietly, and sitting doing deskwork. The intensity of AS was considered equal to the MET value of multiple household tasks. The intensity of walking and running was considered equal to the MET value of walking at 2.5 $miles \cdot h^{-1}$ (4.0 $km \cdot h^{-1}$), and of running at 6.7 $miles \cdot h^{-1}$ (10.8 $km \cdot h^{-1}$), respectively. The intensity of cycling was considered equal to the weighted on speed average of MET for cycling between 10 and 11.9 $miles \cdot h^{-1}$ (16.1 and 19.1 $km \cdot h^{-1}$) and for cycling between 12 and 13.9 $miles \cdot h^{-1}$ (19.3 and 22.4 $km \cdot h^{-1}$). MET_D and AC_D were linearly related ($r = 0.90$, $P<0.001$).

Table 3. Types of activity performed during the day.

Activity type	MET	Minutes·d^{-1}	
		Mean ± SD	Range
Lie	1	513 ± 67	382 – 683
Sit-Stand	1.3	560 ± 111	370 – 683
AS	3.5	128 ± 45	55 – 231
Walk	3	187 ± 55	85 – 291
Run	11	3 ± 4	0 – 14
Cycle	6.7	28 ± 14	8 – 54

MET, metabolic equivalent (20); AS, active standing.

PAL regression models

The model based on AC_D explained 46% of the variation in PAL (r = 0.68, P<0.05) with a standard error of estimate (SEE) of 0.13 or 7.4% of the mean measured PAL (Figure 2A). The limits of agreement between predicted and measured PAL were from -0.243 to +0.245 (Figure 2B). The model based on MET_D explained 51% of the variation in PAL (r = 0.71, P<0.05) with a SEE of 0.12 or 6.8% (Figure 2C). The limits of agreement between predicted and measured PAL were from -0.233 to 0.235 (Figure 2D). None of the physical characteristics of the population was correlated to the residual of these prediction models.

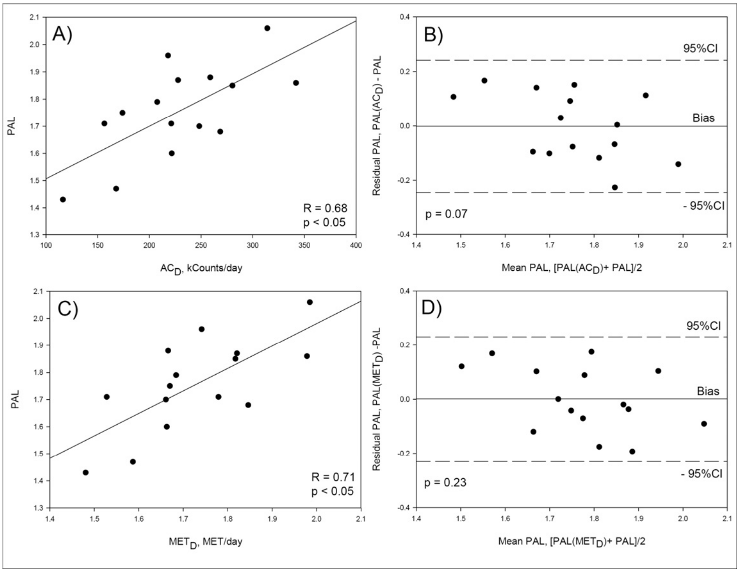

Figure 2. Accuracy of the PAL prediction models based on (A) activity counts a day (AC_D) and (C) metabolic equivalent a day (MET_D). (B and D) Bland-Altman plot of the models.

TEE regression models

The model based on SMR and AC_D explained 85% (r = 0.92) of the variation in TEE, with a SEE of 0.8 $MJ \cdot d^{-1}$ or 6.4%. The model based on SMR and MET_D explained 87% (r = 0.93) of the variation in TEE, with a SEE of 0.75 $MJ \cdot d^{-1}$ or 6%. When basic body characteristics and AC_D were used in the stepwise regression analysis, only BM and AC_D were included in the prediction model, and the explained variation in TEE was 51% (r = 0.71), with a SEE of 1.47 $MJ \cdot d^{-1}$ or 11.7%. The model based on BM and MET_D, explained 60% (r = 0.77) of the variation in TEE, with a SEE of 1.33 $MJ \cdot d^{-1}$ or 10.6%. Considering advanced body characteristics and AC_D, the stepwise regression analysis selected FFM and AC_D in the prediction model of TEE. The explained variation in TEE of this model was 67% (r = 0.82), with a SEE of 1.2 $MJ \cdot d^{-1}$ or 9.6%. When advanced body characteristics and MET_D were used in the stepwise regression analysis, FFM and MET_D were included in the prediction model. The explained variation in TEE of this model was 76% (r = 0.87), with a SEE of 1.02 $MJ \cdot d^{-1}$ or 8.2%. None of the physical characteristics of the population was correlated to the residual of the prediction models. Coefficients, significance level, and partial correlations of all models are summarized in Table 4.

Table 4. Prediction models of TEE.

Dependent	Ind	Coefficient	Par-r^2	Dependent	Ind	Coefficient	Par-r^2
TEE	INT	- 9.3		TEE	INT	- 19.1	
	SMR	2.5**	0.59		SMR	2.5**	0.59
	AC_D	$1.8 \cdot 10^{-5}$**	0.26		MET_D	8.4**	0.28
Model			*0.85*	*Model*			*0.87*
TEE	INT	0.8		TEE	INT	- 8.9	
	BM	0.1*	0.42		BM	0.1*	0.42
	AC_D	$1 \cdot 10^{-5}$*	0.09		MET_D	6.5*	0.18
Model			0.51	Model			0.60
TEE	INT	- 2.4		TEE	INT	- 13.1	
	FFM	0.2**	0.54		FFM	0.2**	0.54
	AC_D	$1.2 \cdot 10^{-5}$*	0.13		MET_D	7.3*	0.22
Model			0.67	Model			0.76

Ind, independent elements in the model; p, significance level; Par-r^2, partial correlation; Model, r^2 of the prediction model; TEE, total daily energy expenditure; INT, intercept; SMR, sleeping metabolic rate; AC_D, activity counts per day; MET_D, daily metabolic equivalent; BM, body mass; FFM, fat free mass.*, P<0.05; **, P<0.001.

AEE regression models

When subject characteristics and AC_D were entered as independent variables in a stepwise regression analysis, BM and AC_D, significantly contributed to the explained variation in AEE. The model explained 47% (r = 0.68) of the variation in AEE, with a SEE of 0.98 MJ·d^{-1} or 21.7%. Moreover, BM and MET_D were selected as significant predictors of AEE. The explained variation in AEE of this model was 60% (r = 0.77), with a SEE of 0.85 MJ·d^{-1} or 20.7%. When advanced body characteristics and AC_D were used in the stepwise regression analysis, FFM and AC_D were included in the prediction model. The explained variation in AEE was 60% (r = 0.77), with a SEE of 0.85 MJ·d^{-1} or 20.7%. Furthermore, FFM and MET_D were selected as significant predictors of AEE. This model explained 73% (r = 0.85) of the variation in AEE, with a SEE of 0.70 MJ·d^{-1} or 17%. None of the physical characteristics of the population was correlated to the residual of the prediction models. Coefficients, significance level, and partial correlations of all models are summarized in Table 5.

Table 5. Prediction models of AEE.

Dependent	Ind	Coefficient	Par-r^2	Dependent	Ind	Coefficient	Par-r^2
AEE	INT	- 3.0		AEE	INT	- 12.4	
	BM	0.05*	0.26		BM	0.07*	0.35
	AC_D	$1.2{\cdot}10^{-5}$*	0.21		MET_D	6.7**	0.25
Model			*0.47*	*Model*			*0.60*
AEE	INT	- 4.9		AEE	INT	- 14.7	
	FFM	0.1*	0.21		FFM	0.12**	0.48
	AC_D	$1.3{\cdot}10^{-5}$*	0.38		MET_D	7.1**	0.25
Model			*0.60*	*Model*			*0.73*

Ind, independent elements of the model; Par-r^2, partial correlation; *Model*, r^2 of the prediction model; AEE, activity energy expenditure; INT, intercept; AC_D, activity counts per day; MET_D, daily metabolic equivalent; BM, body mass; FFM, fat free mass. *, P<0.05; **, P<0.001.

Discussion

This study showed that the identification of types of PA, such as lying, sitting or standing, active standing, walking, running, and cycling, performed during the day combined with a simple methodology to define activity type intensity improved the estimation of TEE, AEE, and PAL as compared to activity counts. The MET_D value was calculated to assess the metabolic cost of PA using the duration and the standard MET compendium value, as presented in literature, of 6 common types of activity, identified using a newly developed classification tree model. MET_D improved the explained variation in PAL by 5% as compared to AC_D. Furthermore, depending on which independent variables were considered to represent differences in body size, the models based on MET_D improved the explained variation in TEE from 2 to 9% and improved the explained variation in AEE by 13%, as compared to the models based on AC_D.

Only a small number of accelerometers have been validated against the gold standard technique of doubly-labeled water. Those that were validated, often showed poor correlations with energy expenditure or the main contribution to the explained variation in TEE, or AEE was determined by subjects' physical characteristics (7). Very few studies reported a higher accuracy in predicting TEE, AEE and PAL than the accuracy of the models obtained in the current study (7, 8, 24). Plasqui et al (8) developed a prediction model of TEE using as independent variables SMR, and AC_D. The explained variation of the model was 90%. In our model based on the same independent variables, the explained variation in TEE was 85%. Carter et al. (24) developed a model to predict TEE using as independent variables body height and AC_D in a population of male young adults. The explained variation of the model was 73% and AC_D accounted for 27% of the explained variation in TEE. Plasqui et al. (8) developed a model to predict TEE using as independent variables age, BM, height, and AC_D in a population of young adults. The explained variation of the model was 83 % and ACD accounted for 19 % to the explained variation in TEE. In our study, TEE was predicted by BM and AC_D. This model explained 51 % of the variation in TEE while AC_D accounted for 9 % to the explained variation in TEE. Although comparing these prediction models is difficult because of the different independent variables included in the regression, it appeared that the ones developed in the current study showed a lower explained variance in TEE. Additionally, the contribution of AC_D to explain the variation in TEE was lower. This was also observed in the models to predict AEE and PAL as compared to the study of Plasqui et al. (8). A limitation of this study was the fact that the habitual PA was determined during a monitoring period of 5 days, while the TEE was assessed in a period of two weeks, according to the doubly-labeled water protocol. This could have determined a decrease in the contribution of AC_D to the explained variation in TEE, AEE and PAL, because of a reduced ability of AC_D to describe PA. However, some studies have shown that as little as 3 to 4 days of monitoring were sufficient to achieve a reliability of more than 80% in measurements of PA using accelerometers (25, 26). In the study of Plasqui et al. (8) the activity monitor was equipped with a piezo-electric acceleration sensor, while in the current study the Tracmor was equipped with a capacitive sensor that allowed the identification of postures by detecting static accelerations. Additional research is required to understand whether the use of capacitive acceleration sensors determined a decrease in the ability of AC_D to account for the explained variance in TEE, AEE, and PAL as compared to the AC_D measured using activity monitors equipped with piezo-electric sensors. Furthermore, it should be also carefully considered a different data processing of the acceleration signal as a confounding factor when comparing the ability of piezo-electric and capacitive sensors in measuring PA.

The MET_D value provided a more accurate assessment of PA as compared to AC_D, since the developed model to predict TEE, AEE and PAL showed a higher accuracy. The calculation of MET_D was based on the use of a newly developed classification algorithm for the identification of types of physical activity performed during the day. The assessment of PA by identifying activity types was hypothesized to improve the estimation of energy expenditure. This assumption was based on the evidence that the relation between energy expenditure and accelerometer output depends on the type of activity performed. A few studies (9, 27) showed that different linear equations could be developed to estimate the MET of activities such as sitting, standing, walking, and housework, using activity counts. Furthermore, a unique linear relationship between activity counts and activity intensity is not suitable for both running and cycling activities. In fact, these two activities generate a diverse amount of activity counts even at a similar level of METs. In this study, the MET_D value accounted for the different contribution of 6 activity types to TEE, AEE, and PAL. This was possible because the assessment of activity intensity was independent from activity counts. The intensity of lying, sitting or standing and AS was assumed to be equal to a specific MET value as obtained from a published compendium of PA (20). The intensity of each walking, running and cycling activity was assumed to be equal to the MET value of walking at 2.5 miles·h^{-1}, running at 6.7 miles·h^{-1}, and cycling between 10 and 13.9 miles·h^{-1}, as these MET values were representative of the activity intensity at the average speed measured during the monitoring period. The only independent variable determining MET_D was the daily duration of the 6 activity types, since activity intensity was considered constant. This might allow the applicability of the prediction models based on MET_D to any method able to accurately detect the daily duration of the types of activity considered in this study. However, a methodology that allows the detection of activity intensity for each activity type and for each activity bout could be considered to further improve the estimation accuracy of TEE, AEE, and PAL. The challenge would be represented mainly by the determination of intensity for sedentary and unspecified dynamic activities, such as Sit-stand or AS, which occupy a large part of the daytime and could importantly contribute to the definition of the metabolic cost of PA (27).

In the literature, some attempts have been made to improve accelerometer-based estimation of energy expenditure by defining specific regression equation to relate the metabolic cost of PA to activity counts for specific groups of activities such as locomotive and lifestyle activities (28), or sedentary, locomotive or housework activities (9, 27). Additionally, non-linear models such as artificial neural networks have been applied to the raw acceleration of the body to improve the prediction accuracy of energy expenditure (29, 30). However, none of these computationally sophisticated techniques have been validated yet in free-living conditions by using, as a reference measure of energy expenditure, doubly-labeled water. In this study, PA was assessed by a MET_D parameter that accounted for the different contribution to the metabolic cost of PA of each identified type of activity. This approach was similar to that implemented in the ActiReg activity monitor to estimate TEE (31). The ActiReg includes 2 accelerometers. They are positioned on the chest and on the thigh to determine body posture and to categorize PA in 3 classes of intensity. Depending on the posture and on the activity intensity a MET value is used to describe the energy cost of PA. Thus, the definition of energy expenditure was derived from information on posture (lying, sitting, and standing), and the intensity of PA. The ActiReg has been validated against doubly-labeled water, and a standard error of 1.24 MJ/day was obtained in the estimation of TEE (31). Therefore, the prediction accuracy was poorer than the one achieved by the models developed using MET_D.

In this study, PAL and AEE were calculated from measurements of TEE and SMR. In literature, TEE is often corrected by resting metabolic rate (RMR) to determine PAL and AEE. The choice of using SMR instead of RMR derived from the fact that measurements of SMR showed a high reproducibility. Indeed, the intra-individual coefficient of variation of SMR measured in a respiration chamber has been estimated to be below 2% (18). Considering that SMR is about 5 % lower than RMR (32), the mean values of PAL and AEE measured in this study were systematically higher than those derived from TEE and RMR. However, the variability in PAL and AEE was not significantly affected by the use of SMR instead of RMR. Thus, the estimation accuracy of the models to predict PAL and AEE was not influenced by the selection of SMR as correction factor for TEE.

In conclusion, identification of activity types combined with standard MET compendium values improved the assessment of energy expenditure as compared to activity counts. Future studies could focus on the development of models to objectively measure the intensity of common types of PA to further increase the accuracy of the energy expenditure estimation.

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Chapter 5

Aspects of activity behaviour as determinant of the physical activity level

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Abstract

This study investigated which aspects of the individuals' activity behaviour determine the physical activity level (PAL). Habitual physical activity of 20 Dutch adults (age: 26-60 years, BMI: 24.5±2.7 kg·m^{-2}) was measured using a tri-axial accelerometer. Accelerometer output was used to identify the engagement in different types of daily activities with a classification tree algorithm. Activity behavior was described by the daily duration of sleeping, sedentary (lying, sitting and standing), walking, running, bicycling and generic standing activities. Simultaneously, total energy expenditure (TEE) was measured using doubly labeled water. PAL was calculated as TEE divided by sleeping metabolic rate. PAL was significantly associated ($P<0.05$) with sedentary time ($r = -0.72$), and the duration of walking ($r = 0.49$), bicycling ($r = 0.77$) and active standing ($r = 0.62$). A negative association was observed between sedentary time and the duration of active standing ($r = -0.87$; $P<0.001$). A multiple-linear regression analysis showed that 75% of the variance in PAL could be predicted by the duration of bicycling (Partial-r^2 = 59%; $P<0.01$), walking (Partial-r^2 = 9%; $P<0.05$), and being sedentary (Partial-r^2 = 7%; $P<0.05$). In conclusion, there is objective evidence that sedentary time and activities related to transportation and commuting, such as walking and bicycling, significantly contribute to the average physical activity level.

Introduction

Physical activity (PA) is frequently recommended to improve health and prevent chronic diseases (1, 2). Increasing the level of PA can reduce the risks associated with obesity and diabetes, such as hypertension, and cardiovascular diseases (2, 3). For this reason, in 1995 the World Health Organization and the Centers for Disease Control and Prevention (4) recommended the engagement in at least 30 minutes of moderate-intensity activity per day to promote and maintain health. A later revision of these guidelines emphasized the importance of combining moderate and high-intensity activities to achieve a high activity level and gain health benefits (5). Complementing these recommendations, decreasing sedentary behaviors has emerged as an important target for health promotion (6, 7). Indeed, the time spent in low-intensity activities has been associated with markers of obesity (8), weight gain (9, 10), and diabetes (10). It also has a negative impact on the physical activity level (PAL) (11). Besides these guidelines, it remains still unclear whether the engagement in high-intensity PA significantly contributes to the PAL. High-intensity PA might discourage the engagement in other types of activities outside the exercise session, and persuade compensatory behaviors which tend to decrease the activity energy expenditure (11, 12). Therefore, understanding the role of the individuals' PA behavior in determining the PAL is essential to design effective intervention strategies to increase PA.

Habitual PA can objectively be assessed in daily life by recording body movements using activity monitors based on accelerometers. These activity monitors, also called accelerometers, are considered to be the most convenient and most reliable tools to measure PA (13). Recently, they have been used in combination with classification algorithms to identify specific human movements (14-18). This classification of activity types is based on the evaluation of attributes (features) of the recorded acceleration of the body with machine learning algorithms. Some studies focused on measuring body movements with accelerometers positioned on different body parts to identify lying, sitting, standing, walking, and running activities, by using neural network algorithms for the activity classification (19). Only recently, developments in activity monitoring allowed the recognition of several types of physical activities with a single waist mounted accelerometer (20-22). This innovative methodology of analyzing accelerometer data can be used to specifically determine the PA behavior, by measuring the daily distribution of various types of activities.

The current study investigated the relationship between the PAL, as assessed using the gold standard technique of doubly labeled water, and the individuals' activity behavior. A novel technique based on a tri-axial accelerometer and a classification algorithm was used to objectively determine PA behavior. Activity behavior was defined as the daily engagement in different types of activity. The purpose was to analyze which types of PA such as sleeping, sedentary behavior (lying, sitting, and standing), generic standing activities (active standing), walking, bicycling, and running determined the PAL.

Methods

Subjects

Twenty Dutch healthy adults (11 men and 9 women) were recruited by advertisement in local newspapers. The study was conducted during autumn, and most of the participants were living in the neighborhood or in the city of Maastricht, The Netherlands. The study was approved by the Ethics Committee of the Maastricht University Medical Center, and written informed consent was obtained from the participants.

Table 1. Subjects characteristics, N = 20 (11 men; 9 women).

	Mean ± SD	Range
Age, y	41 ± 11	26 – 60
Height, m	1.75 ± 0.09	1.57 – 1.89
Body mass, kg	74.8 ± 11.4	54.5 - 103.4
BMI, $kg \cdot m^{-2}$	24.5 ± 2.7	19.6 – 29.5
Fat mass, kg	20.4 ± 6.4	8.4 – 33.2
Fat free mass, kg	54.4 ± 8.3	39.4 – 70.2
SMR, $MJ \cdot d^{-1}$	6.9 ± 0.8	5.5 – 8.2
TEE, $MJ \cdot d^{-1}$	12.2 ± 1.9	9.6 – 15.5
AEE, $MJ \cdot d^{-1}$	4.1 ± 1.2	2.1 – 6.4
PAL	1.77 ± 0.17	1.43 – 2.08

BMI, body mass index; SMR, sleeping metabolic rate; TEE, total energy expenditure; AEE, activity energy expenditure; PAL, physical activity level (TEE/SMR).

Study design

Subjects reported to the laboratory on day 0 at 09h00 p.m. and entered a respiration chamber for an overnight stay. Anthropometric measurements were taken in the morning after an overnight fast. Body mass (BM) was measured on an electronic scale (Mettler Toledo ID1 Plus, Giessen, Germany) to the nearest 0.01 kg. Height was measured to the nearest 0.1 cm (SECA Mod.220, Hamburg, Germany). PA was measured from the morning of day 1 until the morning of day 15. Total energy expenditure (TEE) and PAL were measured during an observation period of two weeks, from day 1 until day 15.

Energy expenditure and PAL

TEE was measured with the doubly labeled water (DLW) method according to the Maastricht protocol (23). After the collection of a background urine sample, subjects drank on the evening of day 0 a weighted amount of $^{2}H_{2}{}^{18}O$ such that baseline levels were increased with 100 ppm for ^{2}H and 200 ppm for ^{18}O. Additionally, urine samples were collected from the second voiding in the morning and a subsequent voiding in the evening of day 1, day 8, and day 15. PAL was calculated as TEE divided by sleeping metabolic rate (SMR). SMR was measured during an overnight stay in the respiration chamber. The room measured 14 m^3 and was equipped with bed, table, chair, freeze toilet, washing bowl, radio, television, and computer (24). Energy expenditure was calculated from O_2-consumption and CO_2-production according to Weir's formula (25). SMR was defined as the lowest observed energy expenditure for three consecutive hours during the night. Room temperature was held constant at 20 ± 1 °C.

Monitoring of physical activity

The motion sensor used was a modified version of the previously validated Tracmor (Philips Research, Eindhoven, Netherlands) (26). The device included a tri-axial accelerometer and recorded acceleration samples 20 times per second. The Tracmor measured 8 x 3.5 x 1 cm and weighed 34.8 g, including the battery. The Tracmor was fixed at the lower back using an elastic belt. The x-, y-, and z-axes of the accelerometer were oriented along the vertical, medio-lateral and antero-posterior directions of the body, respectively. Subjects were instructed to wear the Tracmor during waking hours, except during showering and water activities. A diary was used to report periods in which the subject was sleeping and not wearing the Tracmor during the day. Furthermore, the diary was used by the subjects to self report the duration of discrete bouts of spontaneous bicycling and running during the day.

Identification of activity type

The raw acceleration signal was downloaded to a personal computer and processed to identify types of PA performed during the day. The acceleration signal was segmented in intervals of 6.4 seconds and features of the acceleration were determined for each axis of measurement, e.g. average, standard deviation, peak-to-peak distance, and dominant frequency in the power spectral density (14). A classification tree algorithm was employed to evaluate the features and to classify the acceleration in one of 6 activity classes: lying, sitting or standing (Sit-Stand), active standing, walking, bicycling, and running. The active standing type was defined to represent dynamic activities not related to ambulation performed in the standing position. The classification tree was developed before the current study on a population characterized by a broad range of weight, height and age: 37 men and 43 women, (mean ± s.d. [min.–max.]) weight = 78 ± 20 [51 - 182] kg, height = 1.72 ± 0.1 [1.49 – 1.97] m, age = 42 ± 16 [19 - 71] y, and BMI = 26.2 ± 5.8 [19.2 – 53.9] $kg \cdot m^{-2}$. The calibration was based on data collected during supervised tests. The acceleration measured during lying, sitting, standing, walking, running, bicycling, washing dishes and sweeping the floor was used to calibrate the decision tree. The data collected during the dishwashing and floor-sweeping activities were used to define the active standing category. The data collected during lying, sitting and standing was used to define the sedentary category.

Classification trees are models in which the classification process is defined by a sequence of conditions based on features of the object to classify (27). Figure 1 shows the structure of the developed classification tree and the features selected for the identification of activity types. The performance of the classification tree is presented elsewhere (20).

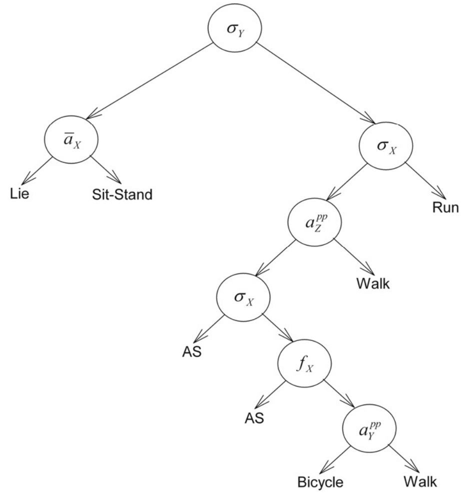

Figure 1. Structure of the classification tree used to identify activity types. The classes identified by the classification tree were: lying, sitting and standing (Sit-Stand), active standing (AS), walking, running, and bicycling. The features employed by the decision tree were: σ_X, σ_Y standard deviation in the x and y axis; $\bar{a}_X$, average acceleration in the x axis; f_X, dominant frequency of the acceleration in the x axis; a_Y^{pp}, a_Z^{pp}, peak to peak distance of the acceleration in the y and z axis. The x, y and z axes correspond to the vertical, medio-lateral, and antero-posterior direction of the body, respectively.

Data analysis and statistics

Monitoring days of PA were considered valid if the non-wearing time, annotated in the diary, did not exceed 150 min·d^{-1}. As a result, the average number of monitoring days was 8 ± 5 days (range: 3 - 14 days). The non-wearing time was removed from the dataset and not used by the classification tree for the identification of activity types. For each subject, PA behavior was defined by the average daily duration (ADD) of sleep, sedentary behavior, active standing, walking, bicycling, and running activity types. The time spent sleeping was determined by the diary annotations. The time spent being sedentary was determined by the sum of the duration of lying, sitting and standing during waking hours. Simple regression analysis was used to examine the relationship between the PAL and ADD of each activity type. The Pearson correlation coefficient (r) was calculated to determine the association between variables. Based on the PAL, subjects were clustered in 2 groups: the highly active group (^{HIGH}PAL; PAL > 1.75), and the less active group (^{LOW}PAL; PAL < 1.75). This PAL value of 1.75 was use as threshold since it represented the average PAL of modern humans, which ranges from 1.5 to 2.0 (28, 29). The Student t-test was performed to identify significant differences in the PA behavior of subjects in the ^{LOW}PAL group compared to that of subjects in the ^{HIGH}PAL group. The Stepwise multiple-linear regression analysis was performed to select the best predictors of PAL among the types of activities that were used to characterize the individuals' behaviour. Since the daily duration of running was not normally distributed, this variable was log transformed. Cook's distance was calculated for each data point to identify influential cases that would impact the result of the regression analysis. All analyses were carried out using Matlab statistical toolbox (The MathWorks, Natick MA) and SigmaStat (Systat software, San Jose CA). Measured parameters are presented as average ± standard deviation (SD). Statistical significance was set to $P < 0.05$.

Results

The mean PAL was 1.77 ± 0.17 (Table 1). On average, PA was monitored for 14.4 ± 1.1 $h \cdot d^{-1}$, which was 92.1 ± 4.5% of the waking hours. The ADD of each activity type describing individuals' behavior is presented in Table 2. A high correlation was observed between reported (rep) and measured (m) ADD of bicycling (rep = 14.8 ± 15.7 $min \cdot d^{-1}$ vs. m = 22.1 ± 14.9 $min \cdot d^{-1}$; $R = 0.77$, $P < 0.001$) and running (rep = 2.1 ± 4.9 $min \cdot d^{-1}$ vs. m = 3.2 ± 4.4 $min \cdot d^{-1}$; $R = 0.81$, $P < 0.001$). As shown in Figure 2, sedentary activities occupied almost 29% of the day (42% of waking hours). As presented in Table 2, PAL was inversely related to the sedentary time, while it was positively associated with the ADD of active standing, walking, and bicycling. The relationship between PAL and ADD of running just failed to reach significance ($R = 0.46$, $P = 0.06$). No significant relationship was observed between PAL and the time spent sleeping ($P = 0.61$). A strong negative correlation was observed between the ADD of active standing and sedentary time ($R = - 0.87$, $P < 0.001$). No significant relationship was observed between the ADD of the other activity types.

Table 2. Average daily duration of each activity type and their correlation with physical activity level (PAL)

Minutes per day	Mean ± SD	Range	Correlation vs PAL	
Sleep	501.2 ± 36.3	429.3 – 548.6	R = - 0.12	P = 0.61
Sedentary	393.2 ± 154.6	84.1 – 663.9	R = - 0.72	P < 0.001
Active standing	367.4 ± 150.4	138.4 – 678.6	R = 0.62	P < 0.01
Walk	71.5 ± 23.6	29.0 – 117.1	R = 0.49	P < 0.05
Bicycle	22.1 ± 14.6	3.5 – 56.5	R = 0.77	P < 0.001
Run	3.2 ± 4.3	0 – 14.3	R = 0.43	P = 0.06

Sedentary, sedentary behavior: lying, sitting and standing still; R, Pearson correlation coefficient; P, significance level.

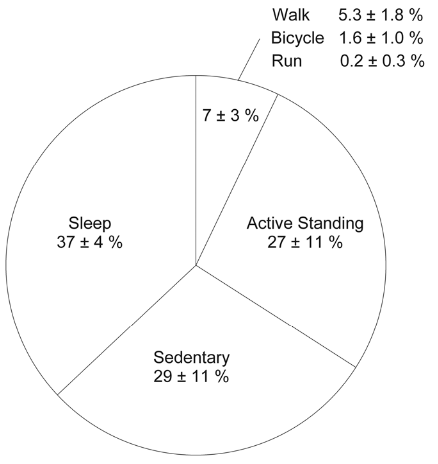

Figure 2. Daily distribution of the types of activity characterizing the individuals' behaviors. Percentage values represent the proportion of the 24 hours day spent on each activity type. Sedentary, sum of lying, sitting, and standing still during waking hours; AS, active standing.

Ten subjects (6 males and 4 females; age: 43 ± 12 y; BMI: 24.4 ± 2.8 kg·m^{-2}) had a PAL < 1.75 and were used to define the ^{LOW}PAL group, while 10 subjects (5 males and 5 females; age: 40 ± 11 years; BMI: 24.5 ± 2.8 kg·m^{-2}) had a PAL > 1.75 and were included in the ^{HIGH}PAL group. A significantly different PA behavior was observed between the ^{HIGH}PAL and the ^{LOW}PAL groups. As shown in Figure 3, the ^{HIGH}PAL group spent significantly less time sedentary than the ^{LOW}PAL group, and significantly more time actively standing, walking, and bicycling.

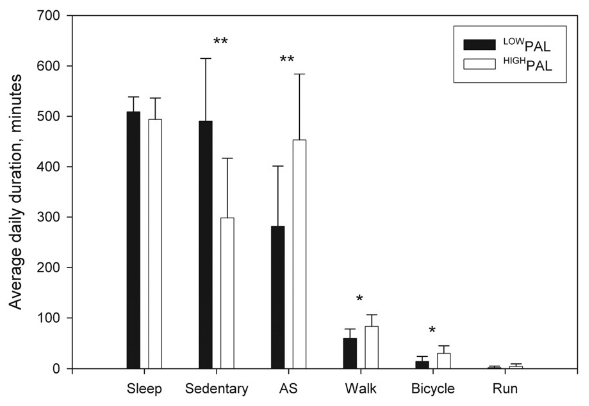

Figure 3. Activity behaviour of subjects belonging to the ^{LOW}PAL group compared to that of the ^{HIGH}PAL group. AS; active standing. **; P < 0.01. *; P < 0.02.

The stepwise multiple-linear regression analysis showed that the best predictors of PAL were the ADD of bicycling (Partial r^2 = 59%; P < 0.01), walking (Partial r^2 = 9%; P < 0.05), and the sedentary time (Partial r^2 = 7%; P < 0.05). The model explained 75% of the variance in PAL, and the coefficients of the multiple-linear model are presented in Table 3. The Cook's distance did not indicate any observation as being an outlier or having an intolerable influence on the result of the regressions (distance < 0.2).

Table 3. Physical activity level (PAL) model developed using the stepwise multiple-linear regression algorithm

Dependent	Independent	Coefficient	Partial r^2	P
PAL	Intercept	1.655		
	Bicycle	0.0053	+ 59 %	< 0.01
	Walk	0.00205	+ 9 %	< 0.05
	Sedentary	- 0.000385	+ 7 %	< 0.05

Dependent, dependent variable; Independent, independent variable; Partial r^2, increase in the explained variance of the model; P, significance level of the increased r^2.

Discussion

To our knowledge, this is the first study to report on a relation between the daily activity behavior and the PAL as measured using DLW. The results showed that the characteristics of the PA behavior that mainly determined the PAL were the sedentary time, and activities related to transportation such as walking and bicycling. In particular, the sedentary time negatively affected the PAL, while walking and bicycling played a determinant role in increasing the PAL. Sleeping appeared not to be associated with PAL. Generic standing activities such as household tasks were significantly associated to PAL. In addition, the high negative co-linearity observed between the daily duration of active standing and sedentary behavior shows evidence for a complementary nature between these two characteristics of activity behavior. This was also observed in a study of Healy et al (30), where the objectively measured time spent in light-intensity activities was inversely related with the time spent being sedentary. The time spent running was positively associated with the PAL but the relation just failed to reach significance (P = 0.06).

The innovative methodology used to monitor PA, based on one accelerometer and a classification algorithm, was used to objectively determine the engagement in different types of activity. Six activity classes were considered and they were selected to represent common types of daily PA. The lying, sitting and standing classes were defined to represent static postures. The walking and running classes were defined to represent gait and ambulation. The active standing class was defined to represent human movements performed in the standing position not related to ambulation. Additionally, the bicycling class was considered since bicycling is not only engaged in for sport practice, but mainly for transportation purposes. In fact, in The Netherlands, bicycling is the favorite means of transport for trips up to 7.5 km (31). This represented a unique feature of the employed accelerometer, as many commercial devices measure PA irrespectively of the type of activity performed, resulting in inaccurate estimations of the amount of PA scored during certain activities such as bicycling.

Only few other studies have objectively measured duration of different type of activities in daily life in combination with DLW measures of PAL. Johannsen et al. (32) monitored PA in a population of lean adult women for 4 days, using the intelligent device for energy expenditure and physical activity (IDEEA). Compared to our results, sitting and standing had a longer daily duration (890 $min \cdot d^{-1}$ vs. 760 $min \cdot d^{-1}$; [sedentary + active standing]), and the engagement in walking, running, and stepping was shorter (48 $min \cdot d^{-1}$ vs. 75 $min \cdot d^{-1}$; [walk + run]). This difference cannot be explained by a different activity level of the two study populations. Indeed, the average PAL measured over a period of 14 days was similar to the average value obtained in the current study. Thus, a possible explanation of the differences in PA behavior could be found by considering the different measurement systems employed. Possibly, the PA recorded using IDEEA could have been biased towards a more sedentary behavior. The limited wearability of IDEEA, which consists of 5 accelerometers connected by wires, compared to Tracmor could result in an increased burden on the subjects and this might have discouraged their engagement in normal PA. Harris et al. (33) using the PAMS activity monitor measured posture and allocation in adult young and elderly subjects. The adult young population was lying for 530 $min \cdot d^{-1}$, was sitting for 426 $min \cdot d^{-1}$, and was standing (still or actively) for 500 $min \cdot d^{-1}$, on average. These values are in agreement with the findings of our study, where the active standing, walking, bicycling and running duration (464 $min \cdot d^{-1}$) is considered to represent the standing class of Harris et al. The PAL of the study population as measured using DLW was 1.73, so the correspondence in PA behavior is confirmed by this similarity in PAL.

PA represents one of the main components of daily energy expenditure (29). Genetic and environmental factors contribute to explain the inter-individual variability in PA (34). The current study showed that some aspects of PA behavior determined the PAL. Locomotion and transportation activities such as walking and bicycling were positively associated with PAL. Sedentary time affected the mean PAL negatively. This implies that an efficient way to increase the activity level is represented by engaging in more physically active transport, spend relatively more time walking and bicycling, and reduce the amount of time spent in sedentary behaviors at work, at home and during leisure time. These findings are in line with the evidence suggesting that contemporary changes in transport, occupations, domestic tasks, and leisure activities have had negative effects on the activity level. According to the multiple-linear regression model, replacing daily 30 minutes of sedentary time with walking increases the PAL by 0.07, which represents about 5% of the average PAL (= 1.75), while 30 minutes per day of bicycling instead of sitting in a car would result in twice the increase in PAL, i.e. 10% of the average PAL. Reaching a PAL of 1.75, given the walking and bicycling duration equal to the average duration registered in this study, requires to limit the sedentary behavior to 7.5 $h \cdot d^{-1}$. This could be achieved, for instance, by developing specific strategies to interrupt prolonged sitting time with active breaks (35). It would not only be helpful to achieve a higher activity level but also to reduce risk for cardiovascular diseases (36), metabolic syndrome (37), weight gain (9), and all cause of mortality (38). Indeed, epidemiological evidence has shown a positive relationship between certain patterns of inactivity, disease outcomes and mortality risk (39). Moreover, intervention studies have recently identified specific cellular mechanisms, activated during the contractile activity of postural skeletal muscle, involved in the regulation of risk factors for disease (40). Therefore, intermittent activities during prolonged sedentary time could be considered as a functional strategy for increasing energy expenditure and improving health by stimulating physiological effects generated by muscle contraction during low-intensity activities (39).

We recognize limitations in this study. Firstly, it could be argued that the number of days considered for the assessment of the PA pattern was on average short. However, some studies showed that 3 to 4 days of monitoring were sufficient to achieve a reliability of more than 80% in measurements of PA using accelerometers (41, 42). Therefore, measuring PA for an average of 8 consecutive days, as in the current study, seems reasonable for a reliable assessment of the habitual PA. Secondly, errors in the identification of activity type could determine incorrect assessment of the ADD of the different activities. However, the classification model showed high classification performances, and classification errors were infrequent. Another limitation of this study might be the reduced number of subjects included. However, the study population was carefully selected to be characterized by a broad BMI range. Moreover, the participants covered the range of normal daily life activity levels, as indicated by the measured PAL range which was 1.43 to 2.08, but were not highly physically active. Indeed, a PAL of 1.43 reflects sedentary lifestyles (28), a PAL of 2.08 represents more active lifestyles (11), and highly active lifestyles are characterized by PAL of 2.5 (28).

Perspectives

In a group of healthy Dutch subjects, there is objective evidence that sedentary time and activities related to transportation and commuting, such as walking and bicycling, significantly determine the average physical activity level. Efficient strategies to increase the activity level may target these aspects of the individuals' activity behavior to promote physical activity and the associated health benefits.

Disclosure

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Chapter 6

Effect of weight loss on physical activity and activity energy expenditure

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Submitted

Abstract

BACKGROUND: Activity energy expenditure (AEE) is the component of daily energy expenditure which is influenced by the amount of physical activity (PA) performed and by the weight of the body displaced. OBJECTIVE: To analyze the effect of weight loss on PA and AEE. DESIGN: The body weight and PA of 66 obese subjects were measured at baseline and after 12 weeks of 67% energy restriction. PA was measured using a tri-axial accelerometer for movement registration (Tracmor) and quantified in activity counts. Tracmor recordings were also processed using a classification algorithm to recognize 6 common activity types engaged in during the day. A doubly-labeled water validated equation based on Tracmor output was used to estimate AEE. RESULTS: Body weight decreased by 13 ± 4%. After weight loss, activity counts augmented by 9 ± 27% (95% CI: +2, +15), and this increase was weakly associated with the decrease in body weight (r^2 = 7%; P<0.05). After weight loss subjects engaged significantly less in sedentary activities (– 26 ± 90 min/d, P<0.05), and more in walking (+ 11 ± 21 min/d, P<0.05) and bicycling (+ 4 ± 14 min/d, P<0.05). The reduced body weight induced a 0.7 ± 0.3 MJ/d diminution in AEE, while the change in PA induced a 0.1 ± 0.4 MJ/d increase in AEE. Consequently, AEE decreased by 0.6 ± 0.4 MJ/d after weight loss. On average, a substantial 55% increase in activity counts was able to restore baseline levels of AEE. CONCLUSIONS: After weight loss PA increases but the energy cost of this increased PA is not as much as the reduction in AEE due to the lower body weight.

Introduction

Obesity is caused by a chronic imbalance between energy intake and expenditure. It has been reported that the amount of energy expended during physical activity plays an important role in preventing weight gain (1-3) and weight re-gain after weight loss (4-6), but contradictory results have been also presented (7). Low levels of physical activity associated with modern sedentary lifestyles have been implicated in the etiology of obesity (2, 3, 8). Obese children and adolescents are less physically active than their normal-weight peers (9). Similarly, obese subjects spend more time sitting and engage in less activity than age-matched lean controls (4, 10). Despite this difference in the level of engagement in physical activity, the activity thermogenesis, also called activity energy expenditure (AEE), is similar between lean and obese individuals (4, 9-12), even when appropriate adjustments are made for differences in body size (9, 12). The reason is that AEE depends not only on physical activity, but also on the weight of the body displaced during movements. Previous studies showed that the energy cost of weight-bearing activities, such as walking (13), and of light-intensity activities (14) was proportional to body weight. This means that obese subjects consume significantly more energy than lean ones in performing the same physical task, which might be why they are less physically active.

Understanding the relationship between obesity and physical activity is limited by the fact that physical activity is difficult to assess under free-living conditions (15). Indeed, physical activity is a complex human behavior which is characterized by multiple factors such as intensity, duration, frequency, and type (16). Some of the most frequently used methods of quantifying physical activity in daily life are motion sensors and doubly-labeled water. Motion sensors can directly measure physical activity by recording body movement (15, 17) and can also be used in combination with classification algorithms to identify types of activities performed (10, 18-20). Doubly-labeled water (DLW) represents the gold-standard technique for measuring energy expenditure in daily life and, combined with information on basal metabolic rate (BMR), can be used to determine AEE in free-living conditions. However, comparing the amount of physical activity between individuals requires a correction of AEE for body size (21).

Whereas lean and obese individuals show similar levels of AEE, reduced-obese subjects have a lower AEE. This was observed in many studies analyzing the effect of physiological adaptation to energy restriction (22-26). Interpreting doubly-labeled water data, Redman et al. (25) concluded that the reduced AEE following weight loss was caused by a lower cost of physical activity and by reduced physical activity. However, motion sensors have seldom been used to measure body movement before and after weight loss. They can provide a more direct measure of physical activity and could help our understanding of why reduced-obese subjects cannot adapt their behavior to reach levels of AEE similar to those of lean and obese subjects.

In this study habitual physical activity was measured in a population of obese subjects using a motion sensor at two different levels of body weight. The motion sensor was an accelerometer able to quantify the total amount of physical activity as well as the individuals' activity behavior. This accelerometer had a number of unique features. Firstly, it has been extensively validated against doubly-labeled water (15), and the measured activity counts proved to correlate highly with measures of energy expenditure in daily life (19). In addition, a classification algorithm was developed to process the raw acceleration signal for the purpose of identifying daily engagement in common types of activity such as lying, sitting or standing, actively standing, walking, bicycling, and running (18). The aim was to investigate the effect of weight loss on physical activity and AEE, and to analyze how much physical activity was required to compensate for the decrease in AEE following weight loss.

Methods

Subjects

A total of 70 subjects were recruited to participate in this study. Inclusion criteria were age 25-70 years and BMI >27kg/m^2. Exclusion criteria were underlying malignity, cancer, HIV infection, psychiatric disease, more than 10% reduction in body weight during the previous 6 months, and women who were pregnant or breastfeeding. Of the 70 participants who started, 4 subjects dropped out. Two participants stopped due to personal reasons, and two were excluded from the analysis due to malfunction of the motion sensor or because of too little monitoring time of physical activity. The final study population consisted of 66 subjects, 10 males and 56 females. The medical ethical committee of the University Medical Center Groningen approved the study. All participants gave written informed consent.

Protocol

After two weeks of weight maintenance, subjects followed for 12 weeks a prescribed weight loss diet providing a 67% energy restriction from baseline energy requirements. At the end of the weight loss phase, subjects underwent another weight maintenance period of two weeks. The energy requirement for weight maintenance was calculated for each participant individually based on the Harris-Benedict equation for estimation of basal metabolic rate, and multiplied by a hypothesized physical activity level (PAL) of 1.5 for total energy expenditure. Participants visited the laboratory at the beginning and end of the first weight maintenance phase, and at the beginning and end of the second weight maintenance phase, which followed the weight loss phase. Measurements of subjects' physical characteristics with the exception of body height were taken at each scheduled visit. Body weight (BW) was measured with subjects in underwear after an overnight fast, using a calibrated hospital scale to the nearest 0.1 kg (model BC-418, Tanita, Arlington Heights, IL). Height was measured to the nearest 0.1 cm (model 240 stadiometer, Seca, Hamburg, Germany). Baseline values were defined as the average values measured at the beginning and end of the first weight maintenance phase. Values after weight loss were defined as the average of the values measured at the beginning and end of the second weight maintenance phase. The physical activity was monitored during the two weight maintenance phases, i.e. at baseline and after weight loss.

Physical activity and activity energy expenditure

Physical activity was monitored using a tri-axial accelerometer for movement registration (Tracmor, Philips Research, Eindhoven, The Netherlands) (18, 19). This instrument was a small 8 x 3.5 x 1 cm lightweight device (34.8 g, including battery), which was placed on the lower back of the subjects by means of an elastic belt. The Tracmor was equipped with a capacitive tri-axial accelerometer able to collect information about both the static and dynamic components of the acceleration forces acting on the sensor. This feature was helpful in identifying types of physical activity and body postures by collecting specific information about the device orientation. The sampling frequency of the accelerometer was set to 20 Hz, and the device was oriented to align the x, y, and z sensing axes to the vertical, medio-lateral, and antero-posterior directions of the body respectively. The subjects were instructed to wear the Tracmor during waking hours, except when showering or during water activities. The subjects were given a diary in which to record the times when they woke up, went to sleep and took off the Tracmor belt during the day.

The Tracmor output was processed to determine total amount of body movement by measuring activity counts, as previously presented (19, 27-30). Tracmor activity counts were calculated over the monitoring period, and the sum of the counts was divided by the number of monitoring days to determine the average activity counts per day (Cnts/d) (19, 31). The AEE was measured using a doubly-labeled water validated equation based on Cnts/d and BW (19).

Identification of activity types

The types of activities subjects performed during the day were identified by analyzing the raw signal measured with the Tracmor. This process involved classifying the acceleration signal by using the knowledge contained in a machine learning algorithm. The acceleration signal was downloaded to a personal computer, segmented into intervals of 6.4 seconds, and characteristics (features) of the acceleration were measured for each axis, such as average, standard deviation, peak-to-peak distance, and dominant frequency in the power spectral density (18). A classification tree is a machine learning algorithm that was used to evaluate the features and classify them into one of 6 activity classes: lying, sitting or standing (sit-stand), actively standing, walking, bicycling, and running. The actively standing type was defined to represent dynamic activities not related to ambulation performed in the standing position. The classification tree was developed in a population characterized by a broad range of weight, height and age: 37 men and 43 women, (mean ± SD [min.; max.]) weight = 78 ± 20 [51; 182] kg, height = 1.72 ± 0.1 [1.49; 1.97] m, age = 42 ± 16

[19; 71] years and BMI = 26.2 ± 5.8 [19.2; 53.9] kg/m^2. The calibration of the classification tree was based on data collected during supervised tests. These supervised tests involved activities such as lying, sitting, standing, walking, running, bicycling, washing dishes and sweeping the floor. The data collected during the dishwashing and floor-sweeping activities were used to define the actively standing category. From the acceleration signal recorded during the standardized activity trial (Figure 1), rules based on acceleration features were learned and used by the classification tree for identifying activity types. These rules are represented by the structure of the classification tree, and the accuracy of the classification tree is presented elsewhere (19).

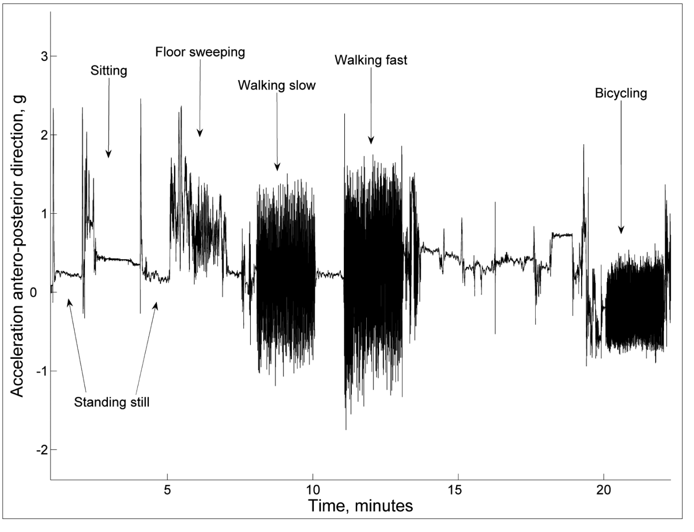

Figure 1. Acceleration signal measured using the tri-axial accelerometer during the trial of standardized activities and used to develop the classification tree. The signal represents the antero-posterior acceleration of the body during different activities and postures.

Statistics and data processing

The paired t-test was used to test significant changes in the measured parameters at baseline and after weight loss. The change in variables was calculated as the difference between the after weight loss value and the baseline value. The stepwise multiple-linear regression analysis was used to identify which subjects' physical characteristics (gender, age, BW, height, BMI) predicted the amount of body movement (Cnts/d) and the daily duration of the 6 types of activity, both at baseline and after weight loss. Additionally, stepwise multiple-linear regression was performed to select the best predictors of the change in total amount of body movement (Cnts/d) registered after weight loss. Environmental temperature and daylight hours were used as independent variables in the stepwise regression analysis to evaluate the contribution of seasonality to physical activity. The results of the regression analysis were expressed in terms of the partial correlation coefficient (Partial r^2), and the regression coefficient (β) of each independent variable of the equation. The AEE doubly-labeled water prediction model was used to determine the independent contribution of the weight loss and of the change in body movement to the change in AEE.

Monitoring days of physical activity were considered valid if the non-wearing time, as annotated in the diary, did not exceed 150 min/d. As a result, the average number of monitoring days was 8 ± 3 days (range: 2 - 14 days) at baseline and 8 ± 3 days (range: 2 - 14 days) after weight loss. The non-wearing time was removed from the dataset and not used by the classification tree for identifying activity type. For each subject, the activity behavior was defined at baseline and after weight loss by measuring the average daily duration of the sleeping, lying, sit-stand, active standing, walking, bicycling, and running activity types. The time spent sleeping was determined by the diary annotations. The lying time was determined by the duration of lying down during waking hours. The running duration was not normally distributed and therefore was log transformed for the statistical analysis. All analyses were carried out using Matlab statistical toolbox (The MathWorks, Natick MA) and SigmaStat (Systat software, San Jose CA). Data in text and tables are presented as average ± standard deviation. The statistical significance level was set to $P < 0.05$.

Results

Subject characteristics of the study population at baseline and after weight loss are presented in Table 1. BW decreased by 14 ± 5 kg during energy restriction. This represented 13 ± 4% of the initial BW. As would be expected from the decreased body size, the AEE estimated using the doubly-labeled water validated equation was significantly lower after weight loss. Despite the decrease in AEE, the amount of body movement was significantly higher after weight loss (Table 1). The measured Cnts/d increased by 9 ± 27% (95% CI: from 2 to 15%), and this increase was weakly associated with the BW change ($\beta < 0$; Partial r^2 = 7%; $P < 0.05$) (Figure 2). Thus: the more weight loss after energy restriction, the higher the physical activity. Stepwise multiple-linear regression showed that the measured Cnts/d at baseline were negatively associated with age ($\beta = -854$; Partial r^2 = 7%; $P < 0.05$) and BMI ($\beta = -957$; Partial r^2 = 7%; $P < 0.05$). After weight loss, the measured Cnts/d were predicted by age only ($\beta = -1333$; r^2 = 18%; $P < 0.05$). No seasonal effect was observed in the regression equations.

Table 1. Subjects' characteristics (n = 66), energy expenditure and physical activity at baseline and after weight loss.

	Baseline	After weight loss	P	95% CI of difference
Subjects' characteristics				
Sex, M/F	10/56	-		
Age, years	51 ± 12	-		
Height, m	1.69 ± 0.08	-		
Body weight, kg	109.5 ± 21.1	95.6 ± 19.6	< 0.001	12.7, 15.1
BMI, kg/m^2	38.3 ± 7.1	33.4 ± 6.3	< 0.001	4.4, 5.2
Energy expenditure				
BMR, MJ/day	7.7 ± 1.4	7.1 ± 1.2	< 0.001	0.5, 0.7
AEE, MJ/day	3.9 ± 1.0	3.3 ± 0.9	< 0.001	0.5, 0.66
Physical activity				
Body movement, kCnts/day	114.1 ± 28.9	122.2 ± 38.1	< 0.05	- 15.8, - 0.4

BMI, body mass index; BMR, basal metabolic rate; AEE, activity energy expenditure; Body movement, physical activity measured using the motion sensor; kCnts/day, kilo (x10^3) counts per day.

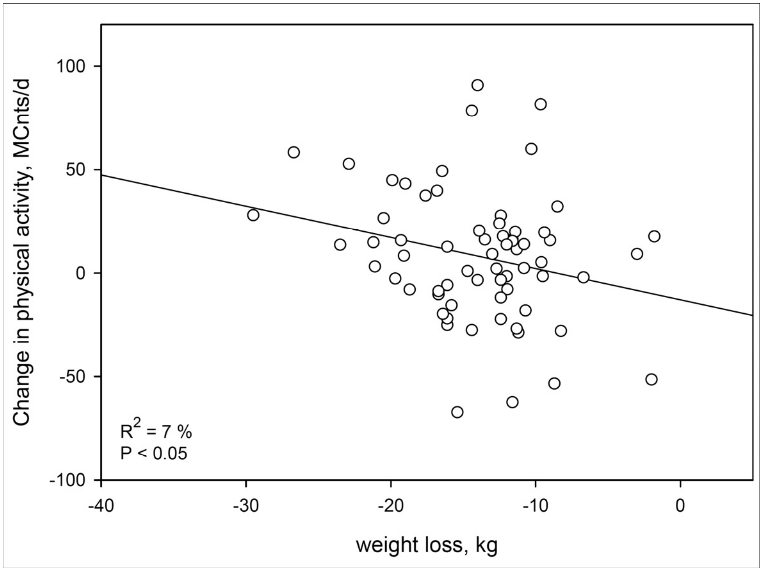

Figure 2. Association between the change in body movement and the change in body weight

The activity behavior, as determined by identifying the types of activity performed, was predominantly sedentary. At baseline, more than 51% of waking time was spent lying, sitting or standing still. On average, 5% of waking time was spent walking. The sitting or standing still time was positively associated with age ($\beta > 0$; r^2 = 11%; $P < 0.01$), while the duration of actively standing was negatively associated with age ($\beta < 0$; $r^2 = 13\%$; $P < 0.01$). The engagement in walking was predicted by age ($\beta < 0$; Partial r^2= 6%; $P < 0.05$) and BMI ($\beta < 0$; Partial r^2= 6%; $P < 0.05$). Thus, once the negative contribution of age to the daily duration of walking is removed, a significant influence of BMI on the amount of time spent walking was observed. The daily duration of sleeping, lying, bicycling and running was not associated with any physical characteristics at baseline (Table 2). The stepwise prediction models showed that age was the only parameter explaining the variability in the duration of sitting or standing, actively standing, and walking, after weight loss, while the daily duration of sleeping, lying, bicycling and running was not associated with any physical characteristics. No seasonal effect was observed in the regression equations (Table 2).

Table 2. Relationship between the daily duration of different types of activities and subjects' characteristics at baseline and after weight loss.

	Baseline		After weight loss	
	Equation	R^2	Equation	R^2
Behavior				
Sleep	n.s	–	n.s.	–
Lie	n.s	–	n.s.	–
Sit-stand	250 + 3 • age	11%	158 + 4 • age	19%
AS	513 – 3 • age	13%	539 – 3 • age	18%
Walk	101 – 0.4 • age – 1.1 • BMI	14%	71 – 0.6 • age	8%
Bicycle	n.s.	–	n.s.	–
Run	n.s.	–	n.s.	–

Equation, results of the stepwise multiple linear regression between subjects' characteristics and daily duration of each activity type; R^2, correlation coefficient of the regression equation; Sit-stand, sitting or standing; AS, actively standing; n.s., not statistically significant.

After weight loss the activity behavior significantly changed: subjects spent less time sitting or standing still (- 26 ± 90 min/d, $P < 0.05$), and more time walking (+ 11 ± 21 min/d, $P < 0.001$) and bicycling (+ 4 ± 14 min/d, $P < 0.05$) (Figure 3). From this behavioral change an average additional energy expenditure of + 0.13 MJ/d could be estimated, assuming the energy cost of sitting and standing, of walking and of bicycling to be equal to1.3 METs, 3 METs, and 6.7 METs (19) respectively ($\Delta AEE = BMR \times [\Delta time_{Sit\text{-}Stand} \times 1.3 + \Delta time_{Walking} \times 3 + \Delta time_{Bicycling} \times 6.7] / 1440$ min/day).

The change in AEE not accounted for by body movement, and, therefore, induced by the change in BW was - 0.70 ± 0.26 MJ/d (95% CI: from - 0.76 to - 0.63). The change in AEE induced by the change in body movement, i.e. not accounted for by BW, was + 0.10 ± 0.38 MJ/d (95% CI: from 0.004 to 0.19). As a result of the change in both BW and body movement, AEE significantly decreased by 0.60 ± 0.40 MJ/d (95% CI: from - 0.70 to - 0.50) after weight loss (Figure 4). According to this model, to compensate for the decrease in AEE due to the change in BW, body movement should have increased by 58 ± 21 kCnts/d (55 ± 29% of the baseline Cnts/d, CI: from 47 to 61%) after weight loss.

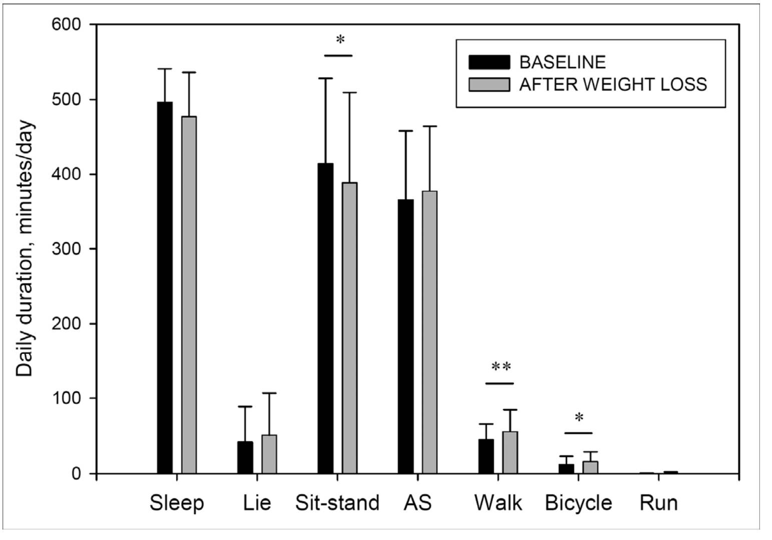

Figure 3. Duration of the types of activity performed at baseline and after weight loss. Sit-stand; daily duration of sitting or standing still. AS; daily duration of actively standing. (*) or (**); significant difference between baseline and after weight loss (P<0.05 or P<0.001).

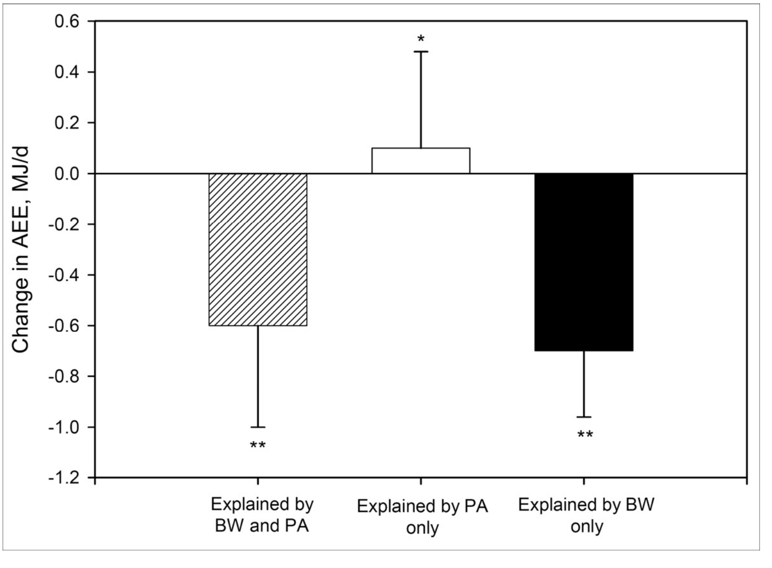

Figure 4. Contribution of the change in body weight (BW) and the change in physical activity (PA) to the change in activity energy expenditure (AEE). (*) or (**); significant difference from zero (P<0.05 or P<0.001).

Discussion

This study showed that weight loss was accompanied by an increase in physical activity. Reduced-obese subjects spent significantly more time walking and bicycling and less time doing sedentary activities. Despite this higher amount of body movement, the AEE was substantially lower after weight loss. The reason was that the reduced cost of physical activity determined by the lower body weight could only be compensated for by a more than 50% increase in physical activity.

The physical activity measured at baseline and expressed as the amount of body movement was inversely associated with age and BMI. This is in line with other studies showing how physical activity decreases with age (32). Additionally, cross-sectional evidence indicates an inverse relationship between physical activity and BMI (33, 34). After weight loss, the relationship between subjects' characteristics and body movement changed significantly. The negative effect of BMI on Cnts/d disappeared. Similarly, the walking time measured at baseline decreased proportionally as BMI increased. After weight loss, we did not observe any negative effect of BMI on walking duration. Furthermore, the augmented walking time measured after weight loss exceeded the value predicted by age and BMI. The duration of walking (56 ± 29 min/d) was significantly higher ($P<0.05$) than predicted (49 ± 7 min/d) using the equation developed at baseline based on age and BMI. This reveals that body size can play a significant role in influencing obese subjects' engagement in physical activity. Ultimately, as shown by the multiple-linear regression analysis, the change in body movement was predicted by the amount of weight loss. This may indicate that high values of body weight could result in impaired bodily function, limiting the ability of obese subjects to perform physical tasks. A number of studies have shown how obesity and excess body weight could impose functional limitations, such as overloading the locomotive system during weight-bearing activities (35), in particular during walking (36), which could potentially limit engagement in physical activity (37). Considering that low levels of physical activity play an important role in the development of obesity by reducing energy expenditure (38), these findings support the hypothesis that inactivity and the accumulation of body weight might reinforce one another in the process of developing and maintaining the obese state.

Many previous studies investigated the effect of energy restriction on physical activity in obese subjects, and the results were contradictory. Weinsier et al. (39) reported that obese women tended to be more physically active after weight loss, which is in agreement with the findings of this study. Others reported no change in physical activity after energy restriction as measured using Doppler-radar monitoring systems in the confined environment of a respiration chamber (23, 24). Accordingly, a proposed theory states that the physical activity is biologically determined and not altered by perturbations in body weight (4). Then, when physical activity was determined using doubly-labeled water, i.e. by correcting energy expenditure for differences in body size, dieting subjects decreased their engagement in physical activity. This was reported in the semistarvation Minnesota study (26) as well as in less severe energy restrictions (22-25). However, interpreting doubly-labeled water data to determine physical activity is controversial. Indeed, AEE is mainly determined by the amount of physical activity and by the weight of the body displaced during movement. The BW relates to AEE depending on the type of activity performed (21). AEE resulting from weight-bearing activities, such as walking and stepping, is directly related to BW (21), while sedentary activities and bicycling result in an AEE which is directly related to BW raised to the power of 0.3 and 0.5 respectively (21). To further complicate the AEE vs. BW relationship, BW influences the amount of physical activity engaged in, and in particular the types of activity performed. This means that a unique correction factor of AEE can hardly be established to determine the amount of physical activity from doubly-labeled water data. Schoeller et al. (14) showed that BW represents a proper correction factor for AEE during light-intensity activities, because the relationship between AEE and BW has a zero intercept and a slope coefficient that is not significantly different than one. Other studies (21, 40, 41) pointed out that BW raised to the power of 0.5 should be preferred to BW when normalizing AEE. The reason was that $BW^{0.5}$ closely resembles the average effect of weight on AEE caused by the activity types usually engaged in during daily life. In our study, combining the results of Prentice et al. (21) with the measurements of the individuals' activity behavior indicates that AEE was linearly dependent on BW raised to the power of 0.35 ± 0.04 at baseline and raised to the power of 0.36 ± 0.04 after weight loss. This highlights the fact that normalization strategies of doubly-labeled water data have poor reliability in determining the amount of physical activity at different levels of body weight.

Obese subjects have comparable levels of AEE to lean ones (4, 10), even if they are generally less physically active (9-12). Reduced-obese subjects, because of the negative impact of weight loss on the energy cost of physical activity, have lower values of AEE compared to both lean and obese subjects (22-24). In this study, only a few individuals (n = 5) could offset the reduction in AEE due to weight loss (change in AEE was + 0.29 ± 0.15 MJ/d) by a 59 ± 27% increase in the amount of body movement (or 65 ± 29 kCnts/d). This was accomplished by reducing the sedentary time by 2 hours/day and by engaging in more physical tasks. The amount of time spent actively standing augmented by about 50 minutes/day, and the walking and bicycling duration also increased, by 30 and 5 minutes/day respectively. The energy budget corresponding to the behavioral change was + 0.70 MJ/d ($\Delta AEE = BMR \times [\Delta time_{Sit\text{-}Stand} \times 1.3 + \Delta time_{AS} \times 3.5 + \Delta time_{Walking} \times 3 + \Delta time_{Bicycling} \times 6.7] / 1440$ min/day), i.e. sufficient to compensate for the decrease in AEE caused by the lower body weight. This means that a substantial effort is required to compensate for the reduced AEE following weight loss by increasing physical activity.

The strength of this study was that for the first time free-living physical activity was measured before and after weight loss using an objective and validated method, which allowed both an assessment of the total amount of body movement and a definition of the individuals' activity behavior. On the other hand, a limitation was that energy expenditure was not actually measured but estimated from prediction formulas based on activity counts and subject characteristics. However, the accelerometer output has been extensively validated against doubly-labeled water and it showed the best performance so far in terms of estimation accuracy of energy expenditure (15). Furthermore, the concept of metabolic efficiency was not considered as a possible determinant of the change in AEE following weight loss. The reason was that currently there is no clear indication of whether weight loss could induce an increase in metabolic efficiency, as defined by the amount of energy per unit of body weight necessary for an individual to perform a certain physical task. Indeed, while a few studies (22, 24) reported changes in metabolic efficiency after weight loss, many others (9, 26, 39, 42) disagree with the hypothesis that weight loss could result in increased metabolic efficiency.

In conclusion, exposure to physical activity is essential to reduce risks for chronic diseases and improve weight maintenance. In this study, we observed that the habitual physical activity in obese subjects was significantly influenced by body weight. The weight loss promoted an increase in the amount of body movement, but this effect could not compensate for the substantial decline in AEE caused by a lower body weight. On average, a 55% increase in the amount of body movement was required to restore AEE to the baseline value. This implied a behavioural change equivalent to a 2-hour reduction per day of sedentary time, and an increase in ambulatory activities. Thus, subjects can offset the weight loss induced decrease in AEE by increasing physical activity, and this certainly contributes to the successfulness of weight maintenance after a dieting program.

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Chapter 7

Low-intensity physical activity can protect against cardiovascular diseases in obese women

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Submitted

Abstract

BACKGROUND: Reduced heart rate variability (HRV) caused by an impaired cardiac autonomic function represents a risk factor for cardiovascular diseases and mortality. This study aimed at analyzing the association between physical activity and HRV adjusted for relevant confounders. METHODS AND RESULTS: Habitual physical activity was measured in 24 obese women (BMI: 41.2 ± 9.1 kg/m^2) using a tri-axial accelerometer by identifying the daily engagement in common activities (sedentary, low-intensity activity, walking, cycling, running) using a classification algorithm. HRV was assessed by spectral analysis of the beat-to-beat intervals at rest. Components at very low (VLF), low (LF), and high frequency (HF) were calculated to evaluate the autonomic modulation of the heart. Measurements were repeated in 12 of the subjects after a 3-months 67% energy-restriction diet. Sedentary time was lower in subjects engaging more in low-intensity activities (r= –.78, P<.001). Independent of age and body weight, the duration of low-intensity activities was positively associated with VLF and LF (r=.53, r=.41; P<.05), while the duration of other activity types was not significantly associated with the adjusted spectral HRV measures. Diet induced a weight loss of 15 ± 5 kg (P<.001) and improved HRV, but improved only VLF to a significant degree (P<.05). The adjusted increase in VLF and LF was associated with an increased duration of low-intensity activities (r =.65 and r=.78, P<.05). CONCLUSIONS: Engagement in low-intensity activities decreased sedentary behavior and independently contributed to improving cardiac autonomic modulation, which can protect against the risk of cardiovascular diseases.

Introduction

Heart rate variability (HRV) analysis has emerged as a reliable, non-invasive indirect method to quantitatively assess cardiac autonomic activity. HRV is a measure of the modulation of the heart that incorporates sympathetic effects, parasympathetic effects, and their interaction. Previous studies showed that high-frequency heart rate fluctuations (HF, 0.15-0.4 Hz) are associated with respiratory sinus arrhythmia, which is a reflection of the parasympathetic tone on the sinus node (1). The low-frequency (LF, 0.04-0.15 Hz) oscillation in heart rate has been attributed to the baroreflex which involves both sympathetic and vagal control (2). Furthermore, it has been suggested that there is an effect by the parasympathetic nervous system on the very low-frequency (VLF, 0.003-0.04 Hz) oscillation of the heart rate as a result of thermoregulatory mechanisms (3), and fluctuation of the renin-angiotensin system (1).

Several studies have reported that low HRV and impaired cardiac autonomic control are associated with increased risk for cardiovascular diseases and mortality in middle-aged and elderly subjects (4, 5), as well as in patient populations (5). This has been explained by the fact that an imbalance in the cardiac activity of the sympathetic and parasympathetic limbs of the autonomic nervous system (ANS) creates a predisposition to cardiac arrhythmias (6), lowers the ventricular fibrillation threshold (7), and catalyzes the arteriosclerotic processes (8), which can lead to coronary heart diseases and sudden cardiac death.

The ANS is not only involved in the modulation of the cardiovascular system, but also plays an important role in the regulation of body weight. In fact, the sympathetic nervous system is implicated in the regulation of energy homeostasis and modulation of glucose and fat metabolism through both direct neural and hormonal effects (9-11). A relationship has been shown between parasympathetic nervous system activity and energy storage (12). Total and regional fat accumulation (11), body mass index (13), and ageing (14) are associated with altered ANS activity. Obese individuals have increased levels of systemic sympathetic activity as compared to lean controls (15-17), but various regional alterations have also been shown (18). Measurements of norepinephrine spillover revealed that obese individuals have a higher sympathetic activity in the kidney, but a depressed cardiac sympathetic outflow (18). Similarly, studies have suggested that HRV is diminished in obesity, predominantly in the VLF and LF components (17, 19, 20), which indicates reduced autonomic control of the heart. Although a high systemic sympathetic tone helps to stabilize body weight and restore energy balance by driving thermogenesis (21), a low cardiac sympathetic and parasympathetic modulation represents a risk factor for cardiovascular diseases and sudden cardiac death, especially when coupled to a high resting heart rate. However, weight loss (22) and regular exercise seem to have a normalizing effect (23).

In this study we aimed at investigating the independent association between habitual physical activity and HRV by cross-sectional and longitudinal examination of a group of obese women before and after weight loss. Physical activity was objectively measured using a tri-axial accelerometer able to quantify both total body movement (24) and the duration of common types of activity performed daily (25), as identified by a classification tree algorithm. Our hypothesis was that habitual physical activity was independently associated with HRV indexes of cardiac autonomic control, and therefore we sought to investigate whether physical activity could independently account for the improvement in HRV indexes following weight loss.

Methods

Subjects

A total of 24 subjects were recruited to participate in this study. Inclusion criteria were female gender, age 25-60 years and BMI >27kg/m^2. Exclusion criteria were underlying malignity, cancer, HIV infection, psychiatric disease, more than 10% reduction in body weight during the previous 6 months, and women who were pregnant or breastfeeding. Subjects completed a standardized questionnaire for past medical history, medication, smoking, and lifestyle. All subjects were non-smokers, in good health and had no evidence of cardiovascular diseases, or diabetes mellitus. None of the participants were taking drugs known to affect the ANS. Subject characteristics are presented in Table 1. The medical ethical committee of the University Medical Center Groningen approved the study. All participants gave written informed consent.

Table 1. Female subjects characteristics.

	Baseline n = 24	After weight loss n = 12	95% CI
Age, y	47 ± 10	46 ± 11	
Height, m	1.70 ± 0.06	1.71 ± 0.07	
Body weight, kg	119.5 ± 26.8	99.8 ± 18.7**	(- 9.9; - 19.3)
BMI, kg/m^2	41.2 ± 9.1	33.6 ± 4.9**	(- 3.4; - 6.5)
Waist circumference, cm	114.6 ± 16.8	96.4 ± 8.6**	(- 8.8; - 14.3)
Fasting plasma glucose, mmol/L	5.8 ± 2.4	5.4 ± 1.8	
Fasting plasma insulin, mmol/L	11.9 ± 7.8	7.8 ± 3.4*	(- 0.1; - 5.6)
HOMA	3.7 ± 4.8	1.9 ± 1.1*	(- 0.04; - 1.45)
Blood Pressure			
Systolic, mmHg	138 ± 15	130 ± 13*	(- 2; - 21)
Diastolic, mmHg	83 ± 8	79 ± 12*	(- 2; - 11)
Heart rate, bpm	78 ± 10	74 ± 9	

*, P < 0.05;
**, P < 0.001;
95% CI, confidence interval of differences (After weight loss - Baseline).

Experimental procedure

Body characteristics were measured at the beginning and at the end of a two-week weight maintenance phase (baseline), during which habitual physical activity was recorded using a tri-axial accelerometer for movement registration. Resting heart rate and HRV were measured at the end of the weight maintenance phase. After a three-month weight loss period measurements were repeated in 12 of the subjects during a second two-week weight maintenance phase. The weight loss was induced by a 67% energy restriction diet. Energy requirements for weight maintenance were determined according to basal energy expenditure, as calculated using the Harris and Benedict formula, and to an average physical activity level (PAL) of 1.5.

Physical activity monitoring

Physical activity was monitored using a tri-axial accelerometer for movement registration (Tracmor, Philips Research, Eindhoven, The Netherlands) during the two weight maintenance periods. This instrument was a small 8 x 3.5 x 1 cm lightweight device (34.8 g, including battery), which was placed on the lower back of the subjects with an elastic belt. The Tracmor has a number of unique characteristics. Firstly, its output has been validated against doubly-labeled water measures of physical activity in free-living conditions (24). Furthermore, Tracmor can be used to identify the types of activity performed during the day. This process involves the classification of the acceleration signal by using the knowledge contained in a machine learning algorithm (25) to identify five activity types: sedentary, low-intensity activity, walking, bicycling, and running (26). The "sedentary" category included static periods of lying down, sitting, and standing still. The "low-intensity activity" category was defined to represent dynamic activities not related to ambulation performed in the standing position, and was developed using data collected during postural transitions, dishwashing, floor sweeping, and other light household tasks. The training of the classification tree was based on data collected during tests conducted in a variety of conditions (e.g. laboratory settings, outdoors, in a gym) and with a population (66 men and 68 women) characterized by a broad range of weight (from 50 to 182 kg), and age (from 17 to 71 years). Detailed information on the working principle of the activity recognition method and of its classification accuracy can be found elsewhere (24, 25). The Tracmor output was processed to determine the total amount of body movement by measuring activity counts per day, as previously presented (27), and to determine the activity behavior by measuring the daily duration of the five activity types identified with the classification tree.

Heart rate measurements

Measurements were performed between 08h00 and 11h00 a.m. Subjects reported to the laboratory at the end of the weight maintenance phase, after an overnight fast. They were asked to avoid physical exercise on the day before the test and to skip breakfast and caffeine drinks in the morning before the test. Measurements were carried out in a dark and silent room, with ambient temperature maintained at between 20 and 22 degrees. After 15 min of rest, subjects were asked to remain supine for 15 min without speaking or making any movements. Subjects breathed at 12 cycles/min (0.2 Hz) by synchronizing their breathing pattern with an electronic metronome rhythm, so that the respiratory rate would influence the HRV indexes of each subject in the same way. ECG was continuously measured for 30 minutes with a three-lead electrode configuration connected to an acquisition system for biomedical applications (Porti, TMSi, Enschede, The Netherlands). The measured ECG was digitalized with a 22 bit analog-to-digital converter, sampled at 2048 Hz, and recorded on a personal computer for post-computation. The digitalized ECG signal recorded during the last 15 minutes of monitoring was processed to identify the QRS complex using a previously presented detection algorithm (28), and to calculate the R-R intervals. The tachogram (R-R intervals vs. beat number) was visually inspected to detect ectopic beats or artifacts causing R-R intervals longer than twice the average. These events were corrected by substituting the R-R interval by a linear interpolation between the previous and the following R-R interval value. HRV was evaluated according to the Task Force guidelines (1). Statistical time domain measures of HRV were determined: mean and standard deviation (SDNN) of the R-R intervals and square root of the squared differences of successive R-R intervals (RMSSD). HRV was also assessed using non-linear methods by quantifying the SD1 and SD2 parameters based on elliptical fitting of the Poincaré plot, indicating vagally mediated R-R interval variability and magnitude of continuous low-frequency R-R interval oscillation (29) respectively. Frequency domain analysis of HRV was performed by calculating the power spectral density of the tachogram using the fast Fourier transform method on 900-second blocks of data resampled at 2 Hz using the Berger algorithm and subjected to a Welch window (256 sec window, 50% overlap). The power spectral density was used to calculate the VLF (0.003-0.04 Hz), LF (0.04-0.15 Hz), and HF (0.15-0.4 Hz) power. Total power and the LF/HF ratio were also computed from the power spectral density. All analyses were carried out using Matlab (Mathworks, Natick, MA), the Matlab Biosig toolbox (GNU general public library, Free Software Foundation, Boston, MA; websource: http://biosig.sourceforge.net/, last access: 01-April-2010), and Kubios HRV software (version 2.0, BioSignal Analysis and Medical Imaging Group, University of Kuopio, Kuopio, Finland).

Body characteristics

Early morning fasting body weight was measured with the subject in underwear using a calibrated hospital scale to the nearest 0.1 kg (model BC-418, Tanita, Arlington Heights, IL). Height was measured to the nearest 0.1 cm (model 240 stadiometer, Seca, Hamburg, Germany). Waist circumference was measured at the site of smallest circumference between rib cage and ileac crest. Systolic and diastolic blood pressure was measured twice using an electronic measurement system (HEM-705IT, Omron Healthcare, Milton Keynes, UK).

Statistics

Subject characteristics were calculated as the average between the values measured at the beginning and at the end of every two weeks of weight maintenance. The paired t-test was used to test significant changes in measured body characteristics and physical activity before and after weight loss. The Pearson correlation coefficient was used to calculate the association between physical activity and body characteristics, and between HRV and body characteristics. To define the unique association between physical activity and HRV, independent of other collinear variables, the partial correlation coefficient was calculated. Multiple-linear regression was also used to assess the independent contribution of parameters descriptive of physical activity in HRV indexes. After weight loss, an independent sample t-test was used to test the hypothesis that the change in HRV relative to the baseline value was significantly different than zero. The frequency domain HRV measures were skewed and therefore were log transformed to satisfy the normal distribution assumption according to the Kolomov-Smirnov test ($P>.20$). The running duration was not normally distributed and therefore was also log transformed for the statistical analysis. All analyses were carried out using SPSS (SPSS Inc., IBM, Chicago, IL). Data in text and tables are presented as average ± standard deviation. The statistical significance level was set to $P< .05$.

Results

Baseline analysis

The activity behavior of the study population was mainly sedentary. More than 45% of waking time was spent lying down, sitting or standing still, while walking and ambulatory tasks occupied on average 7% of waking hours. Sedentary time was strongly and negatively related to the duration of low-intensity activity ($r = –.78$, $P<.001$) (Figure 1). Body weight, BMI, and waist circumference were negatively correlated with the amount of body movement, and with walking time; sedentary time was positively correlated with body weight, BMI, and waist circumference (Table 2). Other types of activity, such as sleeping, low-intensity activities, bicycling and running, were not related to body weight, BMI, or waist circumference. Age seemed to have only a blunted negative effect on physical activity, and the relationship did not reach statistical significance.

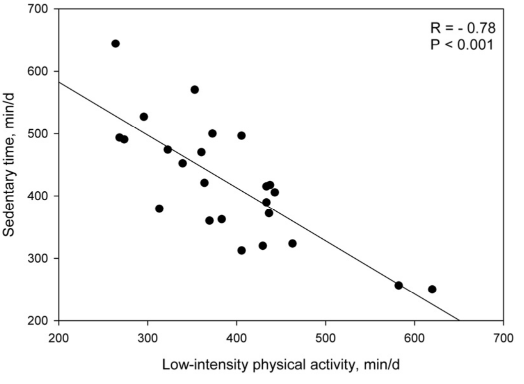

Figure 1. Sedentary time is negatively associated with time spent in low-intensity physical activity.

Table 2. Association between physical activity and subject characteristics.

Baseline (n = 24)	Mean ± SD	Age	BW	BMI	Waist
Physical activity					
Total, kCnts/day	124 ± 33	- 0.28	**- 0.41***	**- 0.41***	**- 0.47***
Activity behavior					
Sleeping, min/d	499 ± 54	- 0.12	- 0.18	- 0.12	- 0.32
Sedentary, min/d	421 ± 96	0.30	**0.41***	**0.42***	**0.53****
LPA, min/d	390 ± 88	- 0.20	- 0.20	- 0.20	- 0.24
Walking, min/d	52 ± 25	- 0.29	**- 0.44***	**- 0.43***	**- 0.46***
Bicycling, min/d	13 ± 9	- 0.17	- 0.15	- 0.20	- 0.11
Running, min/d	0.4 ± 1.5	- 0.10	- 0.15	- 0.16	- 0.21

*, $P < 0.05$;
**, $P < 0.001$;
Values in the table represent the Pearson correlation coefficient between a physical activity parameter and subjects' characteristics; kCnts/min, 10^3 activity counts per minute; BW, body weight; BMI, body mass index; Waist, waist circumference; LPA, low-intensity physical activity.

Temporal and non-linear measures of HRV tended to be negatively associated with body weight and BMI, but the relation failed to reach a significant level (Table 3). Waist circumference was inversely related to SDNN and SD2, indicating an influence on both parasympathetic and sympathetic control of the heart. Frequency-domain HRV measures (VLF, LF, and total power) showed a strong negative association with body weight. Waist circumference was negatively related to all frequency measures of HRV (Table 3). Age seemed to negatively affect the magnitude of HRV, but the association did not reach statistical significance.

Table 3. Association between resting heart rate variability, subject characteristics, and total physical activity.

Baseline (n = 24)	Mean ± SD	Age	BW	BMI	Waist	PA
Time domain measures						
Mean RR, ms	866 ± 131	- 0.05	- 0.28	- 0.24	- 0.17	0.37
SDNN, ms	45.4 ± 40.4	- 0.19	- 0.35	- 0.29	**- 0.43***	**0.48***
RMSSD, ms	30.7 ± 21.7	- 0.26	- 0.23	- 0.15	- 0.29	**0.42***
SD1, ms	21.7 ± 15.3	- 0.26	- 0.23	- 0.15	- 0.29	**0.42***
SD2, ms	59.5 ± 56	- 0.17	- 0.36	- 0.30	**- 0.43***	**0.47***
Frequency domain measures						
Log VLF	2.49 ± 0.6 (309.0 ms^2)	- 0.26	**- 0.40***	- 0.31	**- 0.49***	**0.40***
Log LF	2.27 ± 0.7 (186.2 ms^2)	- 0.27	**- 0.43***	- 0.35	**- 0.56****	**0.40***
Log HF	2.36 ± 0.8 (229.1 ms^2)	- 0.35	- 0.35	- 0.26	**- 0.40***	**0.40***
Log LF/HF	- 0.09 ± 0.1 (0.81)	0.18	- 0.07	- 0.10	- 0.20	- 0.06
Log Total Power	2.94 ± 0.6 (870.9 ms^2)	- 0.33	**- 0.43***	**- 0.35***	**- 0.53****	**0.43***

*, P < 0.05; **, P < 0.001; BW, body weight; BMI, body mass index; Waist, waist circumference; PA, physical activity in activity counts; Mean RR, mean R-R interval length; SDNN, standard deviation of the R-R intervals; RMSSD, square root of the squared differences of successive R-R intervals; SD1 and SD2, parameters of the Poincaré plot; VLF, very low frequency power of the HRV spectrum; LF, low frequency power of the HRV spectrum; HF, high frequency power of the HRV spectrum; Total Power, total power of the HRV spectrum; (geometric mean), is provided for the log transformed variables; Pearson correlation coefficient describes the association between variables.

In unadjusted analyses, the measured physical activity showed a strong and positive association with time and frequency HRV measures (Table 3). However, the partial correlation between body movement and time or frequency HRV measures did not show any statistical significance (P>.05) after accounting for body weight and age. There was a significant relationship between sedentary time and VLF (r = –.49, P<.05), LF (r = –.45, P<.05), and total power (r = –.44, P<.05), but this relationship disappeared after adjustment for age and body weight. The duration of low-intensity activity was positively associated with temporal HRV measures and with VLF (r =.57, P<.01), LF (r =.49, P<.05), HF (r =.41, P<.05), and total power (r =.49, P<.05). After adjusting for age and body weight, there was a significant partial correlation between low-intensity activity and the mean R-R (r =.40, P<.05), SDNN (r =.40, P<.05), RMSSD (r =.55, P<.05), SD1 (r =.40, P<.05), SD2 (r =.55, P<.05), and the VLF (r =.53, P<.05), LF (r =.41, P<.05), and the total power (r =.42, P<.05). The multiple linear regression analysis showed that after accounting for the contribution of age and body weight, the duration of low-intensity activity significantly improved the explained variance of VLF, LF, and of the total power in the prediction models (Table 4). The same results were obtained when the analysis was conducted by adjusting for age, waist circumference, and heart rate (data not shown).

Table 4. Multiple-linear regression models of predictors of HRV.

Model	Coef	SE	Beta	Sig	r^2	Tol	Model	Coef	SE	Beta	Sig	r^2	Tol
Log VLF					*44%*		*Log ∆VLF*					*50%*	
Int	- 0.387	0.925		0.69			Int	- 1.361	0.866		0.15		
Age	- 0.011	0.009	- 0.21	0.24		0.92	Age	0.012	0.013	0.31	0.38		0.57
BW	- 0.006	0.004	- 0.31	<0.05		0.92	∆BW	- 0.045	0.021	- 0.71	<0.05		0.53
LPA	0.003	0.001	0.47	<0.05		0.90	∆LPA	0.008	0.003	0.69	<0.05		0.78
Log LF					*42%*		*Log ∆LF*					*60%*	
Int	0.280	1.215		0.82			Int	0.239	0.927		0.80		
Age	-0.02	0.012	- 0.26	0.16		0.92	Age	-0.02	0.014	- 0.42	0.19		0.57
BW	-0.01	0.005	- 0.40	<0.05		0.92	∆BW	-0.018	0.023	- 0.24	0.45		0.53
LPA	0.003	0.001	0.35	<0.05		0.90	∆LPA	0.012	0.004	0.82	<0.05		0.78
Log TP					*46%*		*Log ∆TP*					*40%*	
Int	0.990	0.985		0.32			Int	0.123	1.07		0.91		
Age	-0.019	0.010	-0.32	0.07		0.92	Age	-0.013	0.016	-0.29	0.45		0.57
BW	-0.009	0.004	-0.41	<0.05		0.92	∆BW	-0.024	0.026	-0.34	0.38		0.53
LPA	0.002	0.001	0.35	<0.05		0.90	∆LPA	0.009	0.004	0.64	<0.05		0.78

Coef, coefficient of the models; SE, standard error; Beta, standardized coefficient; Tol, collinearity diagnostic, if value > 0.1 the effect of variance inflation due to collinear variables could be neglected; Int, intercept of the models; BW, body weight; VLF, very low frequency power; LF, low frequency power; TPower, total power of the beat-to-beat interval spectral density; ∆, indicates change in the variable after weight loss; LPA, low-intensity physical activity.

After weight loss

Energy restriction induced a weight loss of 15 ± 5 kg (Table 1). The amount of body movement was significantly higher than baseline (P<.05, 95% CI: from 1.9 to 23.1 kCnts/day), and the daily duration of low-intensity activity and walking also increased (P<.001, 95% CI: from 29 to 78 min/day; and P<.05, 95% CI: from 3 to 18 min/day respectively). Sedentary time, sleeping, bicycling and running duration did not change significantly. After weight loss, temporal measures of HRV tended to increase but without reaching statistical significance (P>.05). Weight loss induced a significant increase in VLF (P<.05, 95% CI: from 0.02 to 0.62 log10 ms^2) and in total power spectral density (P<.05, 95% CI: from 0.01 to 0.67 log10 ms^2). The LF and HF components of HRV tended to increase after weight loss, but not significantly (P>.05) (Figure 2).

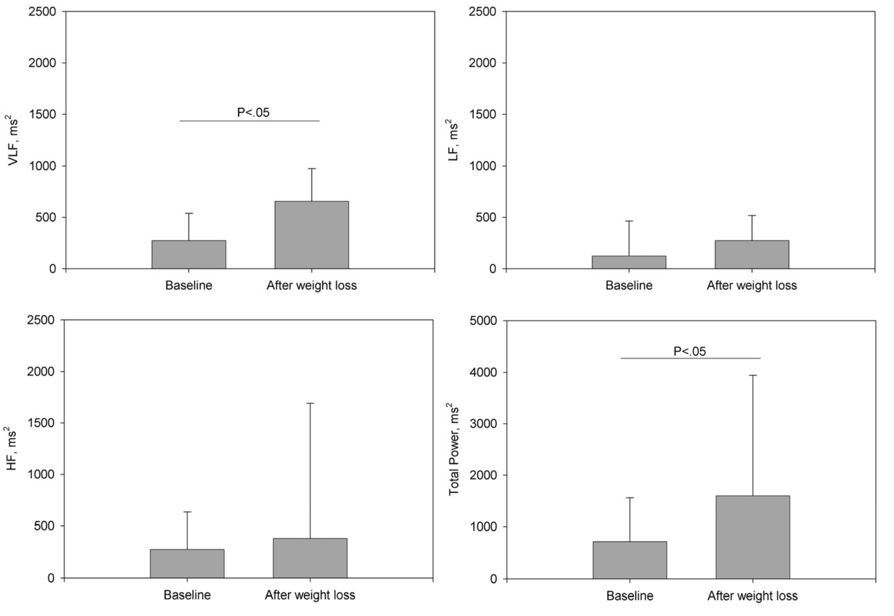

Figure 2. Resting heart rate variability at baseline and after weight loss. Bars represent the median of the variable and the error lines represent the third quartile of the distribution.

Multiple-linear regression models showed that the increase in the duration of low-intensity activities was a significant predictor of the change in VLF, LF, and total power, after adjustment for the change in body weight and age (Table 4). The change in body movement and in the duration of other activity types was not significantly correlated with the adjusted change in HRV measures. Adjusting HRV by waist circumference instead of body weight, and using heart rate as an additional independent variable in the prediction model did not alter the results showing the significant association between low-intensity activity and VLF, LF, and total power (Figure 3).

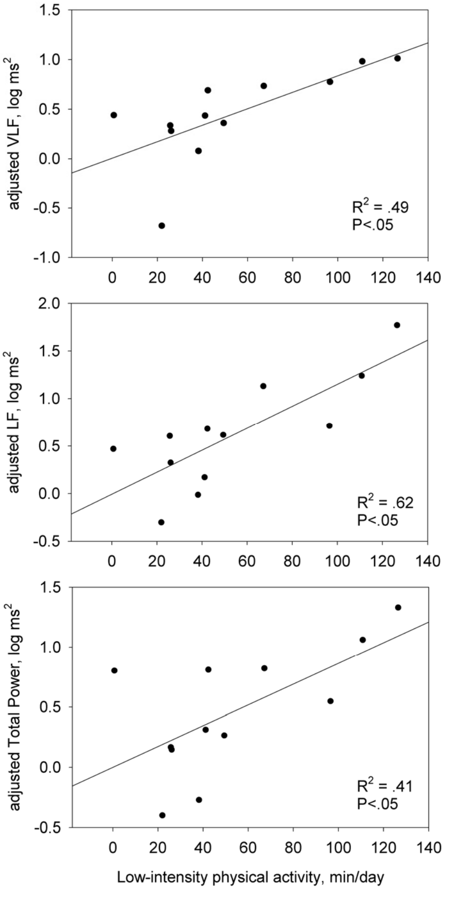

Figure 3. Relationship between the weight-loss-induced changes in low-intensity physical activity and the change in very low (VLF), low frequency (LF), and total power of HRV adjusted by age and body weight.

Discussion

The present study provided two primary findings. Firstly, low-intensity physical activity was independently associated with time and frequency measures of HRV in obese women. Secondly, changes in the autonomic modulation of the heart following weight loss were significantly accounted for by the increased engagement in low-intensity activities. This was also confirmed after adjusting for confounding variables such as age, body weight. The positive contribution of low-intensity physical activity on both VLF and LF components of HRV may indicate a possible involvement of this aspect of individuals' activity behavior in improving thermogenesis and baroreflex sensitivity by the related influences of the autonomic function.

The innovative methodology used to monitor habitual physical activity allowed the objective assessment of the total amount of body movement and of individuals' activity behavior by defining the daily engagement in sedentary, low-intensity, walking, bicycling, and running activities. Previous studies investigating the relationship between habitual physical activity and cardiac autonomic control often used questionnaires to assess physical activity, which is subject to recall biases and overestimation of the activity level (30). A few studies showed how time and frequency domain measures of HRV were greater in active than sedentary age-matched controls (31-33). Furthermore, it has been reported that exercise has a positive effect on cardiac autonomic control, as the magnitude of HRV is greater in endurance trained compared to sedentary individuals34. However, the establishment of a dose relationship between habitual physical activity and HRV has seldom been observed (33, 35). This study showed the fundamental role of low-intensity activities in explaining the association between physical activity and HRV in obese individuals. Subjects engaging in more low-intensity activities were less sedentary and presented proportionally higher values of HRV, especially in VLF and LF, independent of confounding factors such as age and body weight. However, a cause-effect relationship between the duration of low-intensity activity and improved cardiac autonomic control could not be recognized in this study as no specific intervention on physical activity was conducted.

The altered ANS activity in obesity (19) has been attributed to decreased adreno-receptor responsiveness, withdrawal of parasympathetic tone, and increased sympathetic activity (16, 19). There is also a specific relationship between obesity and cardiac autonomic control, as it was shown that elevated body weight causes a reduction in HRV (11, 13, 19, 36). We reported that HRV was lower in subjects with higher body weight and waist circumference, especially in LF and VLF, and tended to decrease with age. Conversely, weight loss improves autonomic control of the heart (36). Grassi et al. (22) explained that this could be due to the improved baroreceptor-mediated effect on heart rate that involves both the parasympathetic and sympathetic limbs of the ANS. Furthermore, an important role in the regulation of cardiac ANS activity is certainly played by insulin resistance. Indeed, hyperinsulinemia, which is often related to insulin resistance, can negatively influence baroreceptor sensitivity (13). The effect of weight loss on hyperinsulinemia can explain the improved autonomic control of the heart. It has been indicated that low levels of plasma insulin concentration reduce systemic catecholamine release by lowering sympathetic tone, which increases adreno-receptor responsiveness and baroreflex sensitivity (37). Yet no cause-effect relationship between sympathetic nervous system activity and insulin resistance in obese individuals has been established (10). Quilliot et al. (13) reported that insulin resistance decreases HRV, especially LF components, by impairing adreno-receptor responsiveness. However, hyperinsulinemia can be reduced not only by energy restriction, but also with physical activity. Indeed, the association between physical activity and plasma insulin concentration is well known (38). Importantly, sedentary behavior and sitting time have recently been shown to play a determinant role in the appearance of insulin resistance (39, 40). Based on the results of our study we can speculate that the mechanism by which low-intensity activity improved HRV in obese subjects was through decreasing sedentary behavior and thus improving insulin regulation, adreno-receptor responsiveness and baroreflex control. Indeed, fasting plasma insulin was positively correlated with the sedentary time and negatively related to the time spent in low-intensity activities (Figure 4).

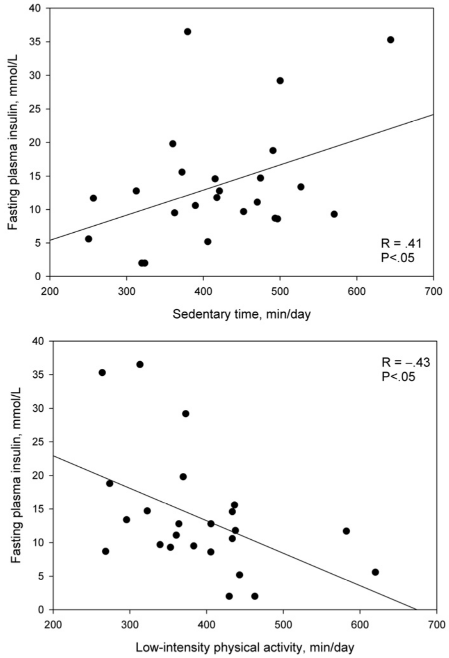

Figure 4. Relationship between objectively measured sedentary time and time spent in low-intensity physical activity and fasting plasma insulin concentration.

Limitations of this study are the number of subjects included in the analysis. This prevented the definition of multiple-linear models with more statistically significant variables. However, the partial correlation analysis adequately allowed correcting for possible confounding factors in analyzing the relationship between physical activity and HRV. Another limitation of this study is that respiratory tidal volume was not measured during resting heart rate measurements. This could have determined the poor relationship between physical activity and the HF component of HRV, which reflects respiratory sinus arrhythmia.

The prognostic significance of HRV in cardiovascular disease has been widely reported (6). Obesity is associated with an increased risk for cardiovascular disease (41), and this has been imputed to the low HRV and high heart rate associated with excess body weight. It has been speculated that modifications in HRV following weight loss involve enhanced autonomic control of the heart due to improved baroreflex control and improved adreno-receptor responsiveness. This is principally triggered by lowered hyperinsulinemia and reduced insulin resistance, which are determined by metabolic processes negatively influenced by adiposity and physical inactivity. In this study we reported that, independent of other relevant confounders, engagement in low-intensity activity significantly accounted for the increased HRV following weight loss in a dose-dependent manner. Future studies should focus on understanding the cause-effect relationship between sedentary behavior, physical activity and HRV to indicate whether increasing low-intensity activity, especially during hyperinsulinemic periods of the day, confers cardio-protective effects in obese subjects.

Disclosure

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Chapter 8

Discussion

Discussion

The focus of this thesis was on investigating perspectives offered by physical activity recognition for improving the assessment of energy expenditure and for developing strategies to promote health. Physical activity recognition was achieved using a single-site accelerometer by identifying lying-down, sedentary-, walking-, running-, cycling-, and generic standing activities. Temporal and spectral features of the acceleration signal carried sufficient information to distinguish six activity types with a high degree of sensitivity and specificity, using a decision tree algorithm.

Traditional methods based on accelerometers quantify the frequency, duration and intensity of physical activity by measuring activity counts. In this thesis it was shown that activity counts measured with the DirectLife tri-axial accelerometer for movement registration ($Tracmor_D$) significantly contributed to explained variation in total energy expenditure (TEE) and activity energy expenditure (AEE) of prediction models developed using doubly-labeled water data. Physical activity recognition further improved the estimation of energy expenditure. Defining a parameter descriptive of the metabolic cost of physical activity by multiplying the daily duration of six activity types, as identified by a classification algorithm, and their hypothetical average intensity was found to explain 9% and 13% greater variation in TEE and AEE, respectively, as compared to activity counts. This indicated that activity recognition represents a novel frontier of development for improving the current methodologies for estimating energy expenditure from accelerometer data by contributing toward eliminating the limitation of the non-uniqueness in the relationship between activity counts and AEE for different activity types.

Accelerometer based physical activity recognition permitted the objective evaluation of the individuals' activity behavior. It revealed that sedentary time and activities related to active transportation, such as walking and bicycling, were determinants of the physical activity level in free-living conditions. Furthermore it was observed, in a group of obese individuals after a 13% weight loss, that at least a 2-hour reduction per day of sedentary time by increasing generic and ambulatory activities is required to restore baseline levels of activity energy expenditure. Finally, the activity behavior of obese subjects was analyzed in relation to markers of cardiovascular health, showing that the time spent each day in low-intensity non-locomotive activities reduced sedentary behavior and improved insulin sensitivity and heart rate variability markers of cardiac autonomic control.

Physical activity recognition

Physical activity recognition represents a novel frontier for improving accelerometer-based physical activity measurements. In **Chapter 3** a classification model was presented to identify three different postures, i.e. lying, sitting, and standing, and three types of locomotion movements, i.e. walking, running, and cycling, by using the acceleration signal recorded with one sensor positioned at the waist. Lying, sitting, walking, running, and cycling were recognized with an accuracy higher than 85%, but standing was often confused with active-standing and sitting and the classification performance was 59%. For this reason in **Chapters 4, 5, 6, and 7** the sitting and standing classes were combined together in a single category describing static events.

Whereas previous studies focused on using multiple-accelerometer systems to identify activity types, in this thesis a single accelerometer was proposed. An integrated activity monitor is less obtrusive than a distributed system, interferes less with the habitual behavior and can be easier implemented in clinical studies. The classification accuracy as achieved with a single accelerometer in earlier studies was often poorer and the number of activity categories identified was smaller than that reported in **Chapters 3 and 4** (Table 1). However, it should be noted that classification accuracy comparisons between studies are complicated by the variety of experimental settings, like placement of accelerometers, number of subjects, and validation method, and by variety of classification procedure, like type of algorithm, features, and activity categories identified as adopted by the different authors. Table 1 clearly shows a trade-off between the number of activity types and the number of accelerometers required for identification. Generic activity categories are classified with a relatively small number of sensors. On the other hand, further specifications such as walking upstairs, or downstairs, and postures such as supine-, prone-, left- or right-side lying, reclining, sitting, and standing requires the use of more accelerometers for the collection of movement information from different body locations (1-4). In previous studies, distinguishing between sitting and standing has been successfully attained with multiple accelerometer systems (2-9). Intuitively, a piezoresistive or capacitive accelerometer located on the upper side of the thigh permits high accuracy for classifying postures. However, this wearing position is adversely affected by the incorrect placement and may be perceived as uncomfortable by users. A potential solution for identifying sitting and standing using one accelerometer is the development of algorithms for classification of postural transition (10). Nevertheless, the level of accuracy achieved for posture classification using multiple-site devices is difficult to attain with a single accelerometer placed around the waist.

Table 1. Studies on physical activity recognition using accelerometers, with information on the number of sensors, placement, and performance with respect to the activities recognized, accuracy, and signal processing.

Reference	Sensors	Placement		Types	Accuracy	Sub	Algorithm	Feat	Validation
Van Laerhoven et al. 2004 (3)	30	Along clothing	10	Sedentary, ambulatory, running, cycling	94%	n.a.	ANN	T	n.a.
Zhang et al. 2003 (4)	5	Chest, thighs (2), feet (2)	32	Postures, gaits, limbs, movement, transitions	> 98%	76	n.a.	n.a.	n.a.
Bao et al. 2004 (1)	5	Arm, wrist, hip, thigh, ankle	20	Ambulatory, households, cycling, sedentary	84%	20	Decision tree	T/F	Video
Bussmann et al. 1998 (2)	4	Trunk, arm, thighs (2)	10	Postures, gaits, running, cycling, transition	88%	3	Threshold	T/F	Video
Bussmann et al. 1998 (5)	4	Sternum, arm, thighs (2)	10	Postures, gaits, running, cycling, transition	90%	8	Threshold	T/F	Video
Foerster et al. 1999 (8)	4	Sternum, wrist, thigh, ankle	9	Lying, sitting, standing, ambulatory, cycling	67%	24	k-nearest neighbor	n.a.	Observ.
Veltink et al. 1996 (43)	3	Sternum, thighs (2)	7	Lying, sitting, standing, ambulatory, cycling	n.a.	10	Threshold	T	n.a.
Uiterwaal et al. 1998 (44)	3	Thigh, waist (2)	5	Lying, sitting, standing, ambulatory, playing	86%	1	Threshold	n.a.	Video
Zhang et al. 2005 (45)	1	Sole foot	4	Locomotion	>98%	40	ANN	T	Test
Pober et al. 2006 (46)	1	Waist	4	Locomotion, household, sitting	81%	6	HMM	T	n.a.
Staudenmayer et al. 2009 (47)	1	Waist	4	Sedentary, walking, sport, household	89%	48	ANN	T	n.a.
Karantonis et al. 2006 (48)	1	Waist	3	Lying, sitting, walking	74-90%	6	Threshold	T	n.a.
Yang et al. 2008 (49)	1	Upper arm	9	Rest, ambulation, eating, playing, reading	75%	n.a.	Fuzzy-Bayesan net	T	n.a.
Manohar et al. 2009 (50)	1	Ear	3	Lying, sedentary, walking	>99%	18	n.a	n.a.	n.a.
Dijkstra et al. 2010 (51)	1	Waist	5	Lying, sitting, standing, walking, shuffling	80%	20	n.a	n.a.	Video

Types, activity types; Sub, subjects; Feat, features; T, time domain; F, frequency domain; ANN, artificial neural net; HMM, hidden Markov model; n.a., not available; Observ, behavioral observation; Video, video recordings; Test, supervised test.

The validation of an activity type classification model requires testing the reproducibility of the recognition performance in free-living conditions and in subject populations different from the one used for training. Indeed, measuring physical activity in daily life may introduce unexpected variability in the acceleration signal, which leads to poor reproducibility of laboratory classification accuracy. Furthermore, classification errors arise due to between-subject variability in accelerometer output for the same activity. Ideally, a successful classification system should overcome these factors and, using data from a range of previous subjects, allow the accurate identification of activity types from an unseen individual in daily life. Testing the classification accuracy has often been based on cross-validation strategies using the training dataset. Only a few previous studies validated the recognition performance with data from unseen individuals and in free-living conditions, for example by using video observations as a reference measure of activity types (Table 1).

The classification performance of the decision tree presented in **Chapters 4 and 5** has been tested on a population of subjects not used for training purposes, and the correctly classified validation segments were 92%, with activity specific F-scores from 81% to 100%. Validation in free-living conditions was also performed by comparing the classification outcome of the decision tree with a "ground truth" represented by the output of the IDEEA activity monitor in combination with a diary for self-reporting of cycling events, in a population of 16 subjects. The participants in this trial were instructed to wear the Tracmor and the IDEEA activity monitor simultaneously over intervals of 13 hours, from 9 a.m. until 10 p.m., in free-living conditions. The IDEEA was chosen as a reference based on the capacity to identify 32 different activity types with a nearly 100% classification accuracy (4). The amount of correctly classified non-locomotive, walking, running, and cycling segments was 93%, and there was no significant difference between the Tracmor assessed duration of the activity types and the ground truth (Figure 1). Thus, the decision tree presented in this thesis was a valid algorithm for identifying locomotion activities in free-living conditions and the classification rules applied for unseen individuals.

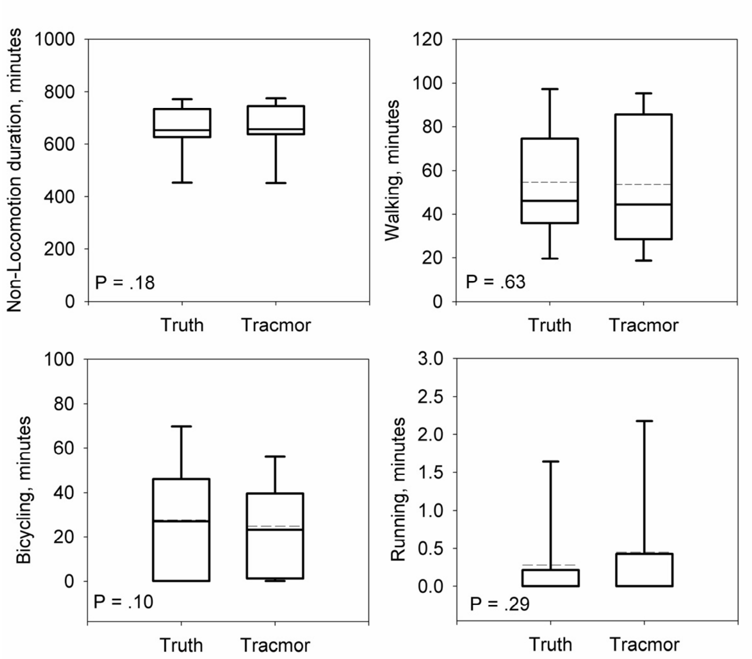

Figure 1. Duration of activity types according to the ground truth (Truth) and to the Tracmor activity recognition model in daily life. Boxes represent median and 25th percentile of the distribution; bars indicate the 5th and 95th percentile; dotted lines represent the mean value of the distribution. P values indicate the paired Student t-test significance level.

Estimation of energy expenditure

Assessment of energy expenditure in free-living conditions is important for determining the relationship between physical activity and physiological outcomes. Multiple-linear models based on activity counts and subjects' physical characteristics have been used to estimate TEE and AEE. In **Chapter 2**, the activity counts measured with $Tracmor_D$ were used to develop prediction models of TEE and AEE using doubly-labeled water data. The activity counts added respectively 16% and 23% to the explained variation in TEE and AEE, after inclusion of subject characteristics. The TEE prediction model based on activity counts and sleeping energy expenditure had a standard error of estimation of 0.9 MJ/day. The AEE prediction model based on activity counts and body weight also had a standard error of estimation of 0.9 MJ/day. A review by Plasqui et al. (11) reported that the majority of the prediction models based on accelerometers' activity counts show poor accuracy, where activity counts often not contribute to explained variation in energy expenditure.

Major limitations of using activity counts to estimate energy expenditure are the non-uniqueness in the relationship between energy expenditure and activity counts for different activity types (12), and the fact that activity counts do not reflect external work performed during physical activity, such as walking on slopes or carrying loads (13, 14). Additionally, missing data and lack of information about fatigue and physical fitness level reduce the estimation accuracy of energy expenditure using accelerometers (15, 16). Several approaches have recently been considered with a view to eliminating these limitations. Firstly, more complex modeling techniques have been used to estimate energy expenditure from accelerometer data. Crouter et al. (17) proposed to predict energy expenditure using a two-regression equation model based on activity counts measured in epochs of 10 seconds. The decision of whether to use a walk/run equation or a lifestyle/leisure time equation was determined by the coefficient of variation of activity counts. Validation of the Crouter method in daily life showed a non-significant difference compared to doubly-labeled water assessed TEE (18). Rothney et al. (19) used artificial neural networks to process the raw acceleration signal measured during a 24-hour stay in a respiration chamber; the reported difference between measured and predicted TEE was 5 ± 4%, with a mean absolute error of 1.8 MJ/day.

An alternative attempt for improving the assessment of energy expenditure was by combining accelerometers with physiological measurements, such as heart rate (20-24) or body temperature and galvanic skin response (25). However, validation of these methods in free-living conditions, using doubly labeled water as a reference measure, is limited. A recent publication by Assah et al. (26) showed that measuring heart rate and acceleration allows accurate estimation of AEE in free-living conditions. However, the independent contribution of acceleration and heart rate to the explained variation in AEE was unclear and the model seemed to benefit from individual calibration. The mean absolute error of the AEE prediction model was 29 kJ/kg/day or 2.0 MJ/day for a 70 kg subject. Zhakeri et al. (24) recently presented a method based on spline interpolation models to estimate energy expenditure using data on body acceleration, heart rate, and subject characteristics. The TEE root mean squared error as measured during a 24-hour stay in a respiration chamber was 0.7 MJ/day. Johannsen et al. (25) showed that the Armband multi-sensor system (BodyMedia, Pittsburgh, PA) could be used to accurately estimate energy expenditure in free-living conditions. The information on skin temperature, galvanic-skin response, and acceleration collected by the Armband, together with subject characteristics, permitted predictions of TEE with a mean absolute error of 0.9 MJ/day. However, the algorithm used by the Armband to predict TEE is unpublished and this hampers the understanding of whether physiological measurements and body acceleration additively and significantly contribute to the TEE estimation. Moreover, the estimation of energy expenditure has been investigated by measuring physical activity using accelerometers placed at different body locations. Combinations of hip and wrist accelerometers have been found to predict energy expenditure in a respiration chamber with higher accuracy than a single-site accelerometer (27).

In **Chapter 4** a study showed that physical activity recognition could significantly improve the estimation of energy expenditure by disentangling the issue of the non-uniqueness of the relationship between activity counts and energy expenditure for different activity types, which is imputed to reduce energy expenditure estimation accuracy (28, 29). The proposed method reduced the TEE root-mean-squared error by 0.15 – 0.20 MJ/day, depending on the model variables. Objective methods to assess activity type intensity, together with activity type recognition, could further improve the TEE prediction accuracy.

Comparing energy-expenditure prediction models is necessary to identify which activity monitor and which modeling technique offers higher estimation accuracy. However, this is challenged by the variety of test protocols, and statistical analysis of the estimation error presented in the different studies. When evaluating the accuracy of a novel motion sensor or prediction algorithm it should be common practice to use doubly labeled water as a reference measure of TEE. The contribution of each independent element in the model should be systematically analyzed to identify source of improved estimation accuracy. The energy-expenditure prediction error should be measured as the standard error of estimation or as the mean absolute estimation error. Reporting the Bland-Altman plot is also important to evaluate the accuracy of a prediction model in the range of measurement. Furthermore, measuring cross-validation errors based on the leave-one-subject-out method is necessary to test the ability of the prediction model in estimating energy expenditure for unseen subjects.

Physical activity recognition has the potential to transform measurement methodologies of physical activity based on accelerometers. Indeed, the outcome of an activity recognition method is directly comparable with any other, upon selection of similar activity categories. This represents a novelty in the field, since accelerometer output is variable among different monitors because of dissimilar sensor type and specifications, i.e. dynamic range, sensitivity, sampling frequency, wearing position, filtering, and integration epoch for the calculation of activity counts. Standardizing accelerometer output helps developing generic prediction models of energy expenditure. For example, the prediction models of TEE, AEE, and PAL presented in **Chapter 4** are applicable to the output of any measurement instrument capable of objectively determining the daily duration of the activity types recognized using Tracmor, assuming that the MET values associated to each activity types are valid for the population under examination.

Physical activity and health promotion

Accelerometer-based physical activity recognition is a feasible method for quantitatively assessing individuals' activity behavior. This technique allows designing tailored physical activity guidelines aimed at increasing physical activity. Current public health guidelines on physical activity recommend the engagement in 30 minutes of moderate-intensity physical activity on five days of the week to promote and maintain health (30). However, these guidelines were developed from assumptions on the effects of regular physical activity rather than on the relationship between dose of physical activity and physiological responses. The reason is the lack of objective and detailed measures on intensity, duration, and type of physical activity. Existing methods like questionnaires, physical activity records, and recall diaries are imprecise, particularly for estimating low levels of physical activity (31, 32); therefore, it was not possible to quantify the dose of physical activity and the related physiological outcomes.

Objective assessment of physical activity using an accelerometer allows the quantification of activity types, duration, and intensity, as well as the activity-related energy expenditure. This information is useful to design intervention strategies to increase physical activity and to determine the physiological outcome related to behavioral change. In a group of healthy adults, sedentary time and engagement in active transportation such as walking and bicycling were significantly related to physical activity level. These aspects of individual behavior should therefore be targeted when defining intervention strategies to increase physical activity in this population (**Chapter 5**). The model developed in **Chapter 5** is unique in its ability to support the design of physical activity guidelines based on the desired physiological outcome. For example, replacing 30 minutes per day of sitting in a car by bicycling can increase PAL by 10%, and energy expenditure, accordingly.

Obese are less physically active than lean individuals (**Chapter 6**). A significant inverse relationship was observed between the time spent walking and BMI, the higher the BMI the longer the sedentary time. After a 13% weight loss, physical activity spontaneously increased. However, because of the positive relationship between body weight and the metabolic cost of physical activity, weight-loss resulted in a decrease in AEE. Objective measurements of the change in activity behavior in this study population showed that only a substantial reduction of sedentary time by an increase in generic low-intensity and ambulatory activities could restore baseline levels of AEE. Furthermore, as presented in **Chapter 7**, increasing the engagement in low-intensity physical activity confers cardio-protective effects. Metabolic processes negatively influenced by insulin resistance, excess body weight, and physical inactivity were counteracted by the engagement in low-intensity physical activity. This indicates that insights into activity behavior are useful for designing intervention strategies for obtaining specific health benefits by increasing physical activity in obese subjects.

There is substantial amount of evidence supporting the role of physical activity in decreasing risk for metabolic diseases (30, 33). Although sedentary time and the duration of other activity types are complementary elements of individuals' behavior, it has been shown that physiological consequences of physical inactivity and activity are qualitatively different (34). Animal studies showed acute and chronic responses to inactivity (35). Bey et al. (35) reported that lipoprotein lipase (LPL) activity, a protein interacting with lipoproteins at the cellular level and involved in plasma triglyceride uptake (36), decreased after 4 hours of physical inactivity in rats as compared with normally ambulating controls and that the condition persisted during the 11 days of test protocol. The mechanism has been identified in the lower degree of contractile activity for skeletal muscles, and confirmed by the observed reduced LPL activity in local muscle areas experimentally prevented from movement (35). This suggests that interventions aimed at decreasing sedentary time and changing a particular pattern of overly sedentary behavior, as suggested in **Chapters 5, 6 and 7**, are mainly useful in patient populations not prone to physical activity to achieve health benefits and prevent the onset of chronic diseases (37, 38). Thus, instruments able to quantify the quality of sedentary behaviors and of low-intensity activities can be of extreme importance for investigating the relationship between physical activity and health.

The successfulness of lifestyle interventions for health promotion can be assessed by monitoring the adherence to certain physical activity guidelines or, more effectively, by examining trends of physiological parameters associated to adverse health conditions. In **Chapter 7**, a study was presented on the relationship between physical activity and the autonomic control of the heart as measured using heart rate variability (HRV) indexes. Reduced HRV has been associated with increased risk for cardiovascular diseases and mortality in the general population. After adjusting for confounding variables, indexes of HRV proved to be independently associated with certain aspects of the activity behavior in a dose-response relationship. Thus, monitoring trends in HRV during lifestyle interventions and providing individualized plans on physical activity to achieve desired levels of HRV represents a highly effective strategy to promote health.

Conclusion

- Tracmor$_D$ is a valid instrument for measuring physical activity and predicting energy expenditure in free-living conditions.
- The acceleration signal measured using a single accelerometer allows accurate recognition of lying, sedentary, activity standing, walking, running, and cycling activities in laboratory and free-living conditions.
- Physical activity recognition improves accelerometer-based estimations of energy expenditure as compared to activity counts.
- Objective assessment of activity type, duration and intensity supports the definition of physical activity guidelines based on desired health outcomes.
- Sedentary time and the engagement in active transportation are major determinants of the physical activity level in healthy adults.
- Obese are less physically active than lean subjects.
- In obese subjects, weight loss increases physical activity but not activity-related energy expenditure.
- Reducing sedentary time to restore baseline activity energy expenditure after weight loss requires a substantial increase in ambulatory and generic low-intensity activities.
- In obese subjects, non-ambulatory activities of low-intensity reduces sedentary time confer health benefits related to lower insulin resistance and improved cardiac autonomic control.

Perspectives

Future studies should explore novel data mining techniques for improving physical activity recognition. For example, clustering techniques and unsupervised learning can help discovering and computing features of the acceleration signal able of distinguishing activity types otherwise difficult to identify. Artificial neural networks, support vector machines and post-classification reasoning models could lead to more accurate physical activity recognition. Furthermore, combining body acceleration with other measurements, such as ambient light, atmospheric pressure, heart rate, and body temperature, could improve the accuracy for activity classification.

The estimation of energy expenditure based on accelerometer measures of physical activity should be tested in different populations to determine the reproducibility of the estimation error on unseen subjects groups. Analyzing the effect of physiological parameters on the estimation error of energy expenditure, such as body weight, age, physical fitness, energy efficiency, and fatigue, could indicate ways to improve TEE and AEE prediction accuracy. TEE and AEE estimation errors can decrease by combining physical activity recognition with activity-type specific equations to relate measures of activity intensity to metabolic costs. Future studies should develop methods to assess intensity for specific activity types using accelerometers data. For example, the relationship between accelerometer output and either walking-, running-, or cycling energy expenditure can be investigated to increase, in combination of physical activity recognition, the prediction accuracy of energy expenditure.

The models presented in this thesis for determining how much physical activity is necessary to achieve certain health benefits, should be tested in intervention studies. For example, the increase in PAL caused by reducing sedentary time and by promoting active transportations should be validated in individuals following a lifestyle intervention and using technology able of quantifying individual behavior and the change in physical activity. Moreover, the effectiveness of population specific guidelines on lifestyle changes should be further investigated. The ability of low-intensity physical activity in reducing sedentary time in obese subjects for health promotion, as measured by heart rate variability or insulin resistance, should be tested in an intervention study.

In the near future, small wearable accelerometers with artificial intelligence, such as physical activity recognition algorithms, and with the ability to non-invasively determine users' metabolic profile, will improve the efficacy of chronic diseases prevention strategies by providing personalized and response-dependent physical activity recommendations.

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Abbreviations

^{18}O	–	Oxigen-18
^{2}H	–	Deuterium
95% CI	–	95% confidence interval
AS, DS	–	Active standing
AAU, AC_D, Cnts/d	–	Activity counts
AEE	–	Activity energy expenditure
AEE/kg	–	Activity energy expenditure adjusted for body weight
ANN	–	Artificial neural network
ANS	–	Autonomic nervous system
a^{pp}	–	Peak-to-peak distance
$\bar{a}$	–	Average acceleration
BEE	–	Basal energy expenditure
BM	–	Body mass
BMI	–	Body mass index
BW	–	Body weight
CO_2	–	Carbon dioxide
DLW	–	Doubly labeled water
AD_D, ADD	–	Average daily duration
ECG	–	Electrocardiogram
FFM	–	Fat free mass
FFT	–	Fast Fourier transform
FM	–	Fat mass
FN	–	False negative
FP	–	False positive
GPS	–	Global positioning system
H	–	Height
HF	–	High frequency index
HMM	–	Hidden Markov model
HRV	–	Heart rate variability
IDEEA	–	Intelligent device for energy expenditure and physical activity
LF	–	Low frequency
LPL	–	Lipoprotein lipase
MET	–	Metabolic equivalent
MET_D	–	Metabolic equivalent per day

O_2	– oxigen
P	– Power spectral density
PA	– Physical activity
PAL	– Physical activity level
^{HIGH}PAL	– High physical activity level
^{LOW}PAL	– Low physical activity level
Partial r^2	– Partial correlation coefficient
PPV	– Positive predictive value
r	– Pearson correlation coefficient
RMSSD	– Root mean square standard deviation
SDNN	– Standard deviation of the R-R intervals
Se	– Sensitivity
SEE	– Standard error of estimation
SEV	– Standard error of validation
Sit-stand	– Sit and Standing
SMR	– Sleeping metabolic rate
TBW	– Total body water
TEE	– Total energy expenditure
TN	– True negative
TP	– True positive
Tracmor	– Triaxial accelerometer for movement registration
$Tracmor_D$	– DirectLife triaxial accelerometer for movement registration
VLF	– Very low frequency
Waist	– Waist circumference
β	– Regression coefficient
σ	– Standard deviation of the acceleration signal

Summary

Strategies for disease prevention often include guidelines on lifestyle changes encouraging participation in physical activity. However, determining what amount of physical activity is necessary for achieving specific health benefits has been hampered by the lack of objective and valid instruments for monitoring physical activity and the related physiological outcomes. This thesis is focused on analyzing the potential advantages offered by accelerometer-based physical activity recognition for improving the assessment of energy expenditure and understanding of the relationship between activity behavior and health.

Physical activity was measured with a tri-axial accelerometer able of recording the raw acceleration signal and determining activity counts, which is the sum of the rectified and integrated acceleration for each sensing axis. Automatic recognition of physical activity types was achieved using a decision tree algorithm capable of processing spectral and temporal features of the raw acceleration signal measured at the waist. The knowledge contained in the classification tree was developed with a training dataset collected during laboratory tests where subjects were asked to perform common types of activities such as lying down, sitting, standing, computer working, cleaning, walking, running, and cycling. The outcome of the classification tree was used to determine individuals' activity behavior by measuring the daily duration of activity types. Total energy expenditure (TEE) was measured with the doubly-labeled water method. Activity energy expenditure (AEE) and the physical activity level (PAL) were determined from TEE and measurements of sleeping energy expenditure in a respiration chamber. The effect of weight loss on physical activity and activity thermogenesis was investigated using a doubly-labeled water validated formula based on activity counts and subject characteristics to determine AEE. Heart rate variability (HRV) analysis was used to evaluate cardiac autonomic balance as an indicator of cardiovascular diseases risk.

It was shown that the activity counts measured with a highly unobtrusive activity monitor, the DirectLife tri-axial accelerometer for movement registration ($Tracmor_D$), were significantly correlated with AEE, and PAL. Regression models based on activity counts predicted TEE with a standard error of estimation from 0.9 to 1.3 MJ/d, depending on the independent variables used to represent differences in body size and composition. Activity counts significantly accounted for 17% to 23% of the explained variation in TEE (**Chapter 2**). Whereas activity counts quantify physical activity duration and intensity, the detection of physical activity types using accelerometer's data allows a qualitative assessment of the activity behavior. A decision tree algorithm recognized lying down, sedentary-, walking-, bicycling-, and running activities with accuracy from 91% to 92%. Thus, temporal and spectral features of the accelerometer output proved to significantly describe differences in the pattern of the signal generated by different activity types (**Chapter 3**). Defining the metabolic cost of physical activity by multiplying the measured daily duration of six activity types by their hypothetical average intensity was found to explain, respectively, 9% and 13%

greater variation in TEE and AEE as compared to activity counts only. This indicated that activity recognition can improve the current methodology for estimating energy expenditure from accelerometer data by contributing toward eliminating the limitation of the non-uniqueness in the relationship between activity counts and AEE for different activity types (**Chapter 4**).

The relationship between the activity behavior and PAL was investigated to determine the importance of certain activity types for achieving a high level of daily energy expenditure. Using an accelerometer-based activity recognition algorithm, it appeared that sedentary time, and the engagement in active transportation, such as walking and bicycling, was significantly related to PAL. Therefore, these aspects of individuals' behavior should be targeted when defining intervention strategies to increase physical activity (**Chapter 5**). Furthermore, in a group of obese individuals, it was observed that the habitual activity behavior spontaneously increased after weight loss. However, AEE markedly decreased, as the increase in physical activity was not sufficient to compensate for the decreased cost for physical activity caused by the lower body weight carried during movement. The study revealed that a significant replacement of sedentary time by generic and ambulatory activities was required to restore baseline levels of AEE (**Chapter 6**). However, this would result in additional health benefits and improve the successfulness of weight maintenance. Accelerometer-based physical activity recognition was used to establish the relationship between individuals' activity behavior and markers of cardiovascular health. Frequency domain measures of HRV were significantly associated with the engagement in low-intensity physical activity as recognized by the classification algorithm during postural transition, household activities and generic movement not related to ambulation. This association was interpreted after observing an inverse relationship between low-intensity activity and sedentary time, and the role of sedentary time in increasing insulin resistance and hyperinsulinemia. Thus, the engagement in low-intensity activities could confer cardio protective effects by lowering fasting-plasma insulin concentration and increasing the autonomic control of the heart (**Chapter 7**).

In conclusion, physical activity recognition was successfully achieved using the signal recorded with a single tri-axial accelerometer and a classification algorithm. Although Tracmor$_D$ showed to be a valid instrument for predicting energy expenditure in free-living conditions, physical activity recognition improved the energy-expenditure estimation accuracy by circumventing issues inherent to the relationship between activity counts and AEE for different activity types. Furthermore, physical activity recognition unraveled which activity types determine the daily activity level, and which behavioral modifications lead to the achievement of higher rates of energy expenditure. In addition, this novel approach to measure physical activity was used to define the dose-response relationship between the engagement in certain physical activity types and HRV indexes, biomarkers related to cardiovascular diseases risks. Thus, advances in accelerometer technology and the introduction of activity recognition models can play a key role in the definition of lifestyle interventions for health promotion, based on response-dependent physical activity recommendations.

Samenvatting

Strategieën voor ziektepreventie gaan soms gepaard met adviezen om de lichaamsbeweging te stimuleren. Door het gebrek aan objectieve en beproefde instrumenten voor het monitoren van lichaamsbeweging en de bijbehorende fysiologische effecten is het echter moeilijk te bepalen hoeveel lichaamsbeweging noodzakelijk is om specifieke gezondheidsvoordelen te behalen. Dit proefschrift analyseert de potentiële voordelen van bewegingsherkenning en registratie met een versnellingsopnemer om een beter beeld te krijgen van het energiegebruik en van de relatie tussen beweging en gezondheid.

Lichaamsbeweging werd gemeten met behulp van een drie-assige versnellingsopnemer waarmee het ruwe versnellingssignaal kan worden geregistreerd en bewegingen kunnen worden gekwantificeerd als de som van de gecorrigeerde en geïntegreerde versnelling voor elke detectieas. Diverse typen lichaamsbeweging werden gedetecteerd door gebruik te maken van een beslisboomalgoritme waarmee spectrale en temporele kenmerken van het aan de romp gemeten ruwe versnellingssignaal kunnen worden verwerkt. Het beslisboomalgoritme werd ontwikkeld met een ‘oefen dataset’, waarvoor proefpersonen werd gevraagd gangbare bewegingstypen te verrichten zoals liggen, zitten, stilstaan, werken op een computer, afwassen, schoonmaken, lopen, hardlopen en fietsen. Aan de hand van het beslisboomalgoritme werd het bewegingspatroon van de proefpersonen berekend in de vorm van de dagelijkse duur van de gespecificeerde bewegingstypen. Gelijktijdig werd het totale energiegebruik (TEE) gemeten met behulp van de tweevoudig gemerkt watermethode. Energiegebruik door beweging (AEE) en het niveau van lichaamsbeweging (PAL) werden afgeleid uit het TEE en metingen van energiegebruik in rust tijdens overnachting in een respiratiekamer. Zo werd een formule gegenereerd om het energiegebruik door beweging te berekenen op basis van de persoonskenmerken lengte, leeftijd, gewicht en geslacht en het gemeten bewegingspatroon. Hiermee werd onderzocht in hoeverre gewichtsverlies van invloed is het energiegebruik door beweging en hoe daarbij de hartfrequentievariatie (HRV) verandert, als indicator voor het risico op hart- en vaatziekten.

Duur en intensiteit van beweging zoals geregistreerd met een makkelijk draagbare monitor, de DirectLife drie-assige versnellingsmeter voor bewegingsregistratie (Tracmor$_D$), bleek een goede maat voor AEE en PAL. De op de bewegingsregistratie gebaseerde modellen voorspelden TEE met een nauwkeurigheid van 0,9 tot 1,3 MJ/dag, afhankelijk van de gebruikte maten voor het weergeven van verschillen in lichaamsgrootte en lichaamsbouw. Bewegingsmeting leverde een significante bijdrage aan de verklaarde variatie in TEE van 17 tot 23% (**Hoofdstuk 2**).

Detectie van het type beweging, naast duur en intensiteit, leverde een verdere verbetering van de voorspelling van TEE. De herkenning van liggen, stilstaan, staan met beweging, lopen, fietsen en hardlopen met het beslisbooomalgoritme had een nauwkeurigheid van 91% à 92%. Frequentie patroon en amplitude van de lichaamsversnelling door beweging, zoals geregistreerd met een versnellingsopnemer, vormden een significant onderscheidend kenmerk voor deze verschillende typen lichaamsbeweging (**Hoofdstuk 3**). De zo gemeten dagelijkse duur van zes bewegingstypen, vermenigvuldigd met hun gemiddelde intensiteit, bleek respectievelijk 9% en 13% méér variatie in TEE en AEE te verklaren dan detectie van enkel duur en intensiteit. Deze verbetering is gebaseerd op correctie voor verschillen in de relatie tussen enerzijds duur en intensiteit en anderzijds AEE voor verschillende typen beweging (**Hoofdstuk 4**).

Meting van type activiteit, naast duur en intensiteit, geeft inzicht in de bijdrage van afzonderlijke activiteiten aan het totale activiteitsniveau. Maatregelen om lichaamsbeweging te bevorderen kunnen zich dan specifiek richten op deze gedragsaspecten. Vermindering van zittende activiteiten ten gunste van vormen van actieve verplaatsing zoals lopen en fietsen dragen het sterkste bij aan een hoger activiteitsniveau (**Hoofdstuk 5**).

Gewichtsverlies resulteert in een vermindering van het activiteitsgebruik door de afname van het te verplaatsen gewicht. Bij een groep personen met obesitas werd vastgesteld dat de gebruikelijke beweging daarentegen spontaan toenam na gewichtsverlies. De bewegingstoename was echter onvoldoende om de energiegebruik verlaging, als gevolg van het geringere lichaamsgewicht dat tijdens beweging wordt meegetorst, volledig te compenseren. De studie liet zien dat nog twee uur rust moest worden ingeruild voor algemene en ambulante activiteiten om het oorspronkelijke AEE te herstellen (**Hoofdstuk 6**). Dit zou de kans op gewichthandhaving na gewichtsverlies bevorderen en ook verdere gezondheidsvoordelen opleveren.

Weinig lichamelijke activiteit met lange rustperiodes is een risicofactor voor hart- en vaatziekten. Hartfrequentievariatie, als indicator voor het risico op hart- en vaatziekten, bleek significant samen te hangen met lichaamsbeweging zoals herkend door het beslisboomalgoritme, tijdens verandering van houding, huishoudelijke activiteiten en algemene beweging (niet gerelateerd aan opstaan). Lichamelijke activiteiten met een lage intensiteit hebben mogelijk al een beschermende werking tegen hart- en vaatziekten door verbetering van de autonome controle van het hart (**Hoofdstuk 7**).

Dit proefschrift beschrijft hoe lichaamsbeweging in verband met gezondheid kan worden gedetecteerd en geregistreerd en geeft voorbeelden van toepassing. Meting van duur en intensiteit van beweging, met één makkelijk draagbaar apparaatje dat rompversnellingen registreert, geeft een betrouwbare schatting van het dagelijks energiegebruik. Type beweging kan betrouwbaar worden gespecificeerd op basis van frequentiepatroon en amplitude van rompversnellingen. Combinatie van activiteitstype, duur en intensiteit geeft een verdere verbetering van de schatting van het dagelijks energiegebruik. Toepassing van deze techniek leidde tot het inzicht dat vermindering van zittende activiteiten ten gunste van vormen van actieve verplaatsing zoals lopen en fietsen het sterkste bijdragen aan een hoger activiteitsniveau. De spontane toename van lichaamsbeweging bij gewichtsverlies is onvoldoende om de energiegebruik verlaging, als gevolg van het geringere lichaamsgewicht dat tijdens beweging wordt meegetorst, volledig te compenseren. Lichamelijke activiteiten met een lage intensiteit hebben mogelijk al een beschermende werking tegen hart- en vaatziekten door verbetering van de autonome controle van het hart. Technologische doorbraken op het gebied van versnellingsmeters en de invoering van bewegingsdetectiemodellen kunnen zo een belangrijke rol spelen bij het nemen van maatregelen ter bevordering van een gezonde levensstijl in de vorm van aanbevelingen omtrent lichaamsbeweging.

Sommario

La prevenzione di malattie croniche necessita spesso interventi sullo stile di vita personale che incoraggino l'attività fisica. Stabilire la quantità di attività fisica necessaria per ottenere specifici benefici di salute é limitato dalla mancanza di validi stumenti di misura e del relativo impatto fisiologico. Questa tesi é focalizzata all'analisi delle potenzialità offerte dal riconoscimento dell'attività fisica attraverso l'utilizzo di un accelerometro, per migliorare la stima della spesa energetica e per rivelare la relazione tra l'attività abitudinaria e la salute personale.

L'attività fisica é stata misurata con un accelerometro triassiale capace di memorizzare il segnale puro di accelerazione e gli *activity counts*, definiti dalla somma dei segnali rettificati ed integrati per ogni asse di misura. Il riconoscimento automatico dei tipi di attività fisica é stato ottenuto utilizzando un algoritmo ad albero, capace di elaborare caratteristiche spettrali e temporali del segnale di accelerazione misurato a livello lombare. Le regole contenute nell'albero di decisione sono state sviluppate utilizzando dati registrati in test di laboratorio, nei quali alcuni individui hanno compiuto diversi tipi di attività comuni, come ad esempio sdraiarsi supini, sedersi, stare in piedi, camminare, correre, pulire, lavorare al computer o andare in bici. L'uscita dell'albero di decisione, rappresentante la durata giornaliera di diversi tipi di attività fisica, é stata utilizzata per determinare le attività abitudinarie dei soggetti misurati durante i test sperimentali. La spesa energetica totale (TEE) é stata misurata utilizzando il metodo di diluizione corporea di acqua marcata con deuterio ed ossigeno-18.

La spesa energetica per attività fisica (AEE) e il livello di attività fisica (PAL) sono stati determinati a partire da misure di TEE e spesa energetica durante il sonno, quest'ultima determinata utilizzando calorimetria indiretta. L'effetto della perdita di peso sull'attività fisica e sulla spesa energetica dovuta ad attività fisica é stata studiata utilizzando una formula per ottenere AEE, basata su *activity counts* e caratteristiche fisiche dell'individuo. Infine, l'analisi della variabilità cardiaca (HRV) é stata effettuata per valutare l'entità del controllo autonomo sul ritmo cardiaco in quanto indicatore di rischio per malattie cardiovascolari.

Questa tesi dimostra che gli *activity counts*, misurati con un dispositivo indossabile per monitorare l'attività fisica (l'accelerometro triassiale DirectLife per la misura del movimento, Tracmor$_D$), sono significativamente correlati con AEE e PAL. Modelli di regressione lineare basati su *activity counts* predicono TEE con errori di stima da 0.9 a 1.3 MJ/giorno, in base al tipo di variabili indipendenti rappresentanti differenze di stazza e composizione corporea. Gli *activity counts* contribuiscono dal 17% al 23% nell'influenzare la variazione di TEE (**Capitolo 2**). Mentre gli *activity counts* quantificano durata ed intensità dell'attività fisica, il riconoscimento dei tipi di attività fisica utilizzando dati accelerometrici permettono un'osservazione qualitativa dell'attività abitudinaria. Un algoritmo di decisione ad albero ha dimostrato di riconoscere attività come ad esempio stare sdraiati, seduti, eretti staticamente, camminare, andare in bicicletta e correre,

con un'accuratezza compresa tra 91% e 92%. Quindi, caratteristiche temporali e spettrali di dati accelerometrici descrivono significativamente le differenze nel pattern del segnale generato dai diversi tipi di attività fisica (**Capitolo 3**).

L'accuratezza dei modelli per la stima della spesa energetica é stata migliorata, definendo il costo metabolico dell'attività fisica moltiplicato per la durata giornaliera di sei diversi tipi di attività per la loro ipotetica intensità. Questo nuovo parametro ha contribuito ad aumentare dal 9% al 13% l'accuratezza dei modelli per la stima di TEE e AEE in confronto a quelli basati su *activity counts*. Ció indica che il riconoscimento dell'attività fisica migliora il metodo tradizionale per stimare la spesa energetica grazie all'utilizzo dei dati accelerometrici. La ragione risiede nell'abilità di modelli basati sul riconoscimento dell'attività fisica di eliminare il problema rappresentato dalla non unicità della relazione tra *activity counts* ed AEE per i diversi tipi di attività (**Capitolo 4**).

L'influenza dell'attività abitudinaria sulla PAL é stata studiata per definire quali tipi di attività assumono particolare importanza nel raggiungere un'alto livello di spesa energetica giornaliera. Con l'utilizzo di un algoritmo di classificazione dell'attività fisica, é emerso che la durata di occupazioni sedentarie e di tipi di attività come camminare e andare in bicicletta, sono significativamente correlate al PAL. Ció suggerisce che questi aspetti dell'attività abitudinaria dovrebbero essere presi in considerazione nel definire strategie per aumentare l'attività fisica e la spesa energetica (**Capitolo 5**). Inoltre, in un gruppo di soggetti obesi, é stato mostrato che l'entità dell'attività abitudinaria aumentava spontaneamente dopo la perdita di peso. Al contrario la AEE diminuiva, a causa del fatto che l'aumento dell'attività fisica non era mediamente sufficiente a compensare il ridotto costo dell'attività fisica determinato dal minor peso corporeo trasportato durante il movimento. Lo studio ha rivelato che nella popolazione esaminata per far ritornare AEE a valori uguali a quelli iniziali, era necessaria una diminuzione delle occupazioni sedentarie sostituendole con attività sia generiche che ambulatorie (**Capitolo 6**). Ció comporta benefici per la salute ma anche un piu'facile mantenimento di peso corporeo dopo una dieta.

Il metodo computazionale usasto per il riconoscimento dell'attività fisica é stato impiegato per stabilire la relazione tra l'attività abitudinaria ed indici della salute cardiovascolare. Misure nel dominio della frequenza della variabilità cardiaca, erano significativamente correlate alla durata di attività a bassa intensità, come identificato dall'algoritmo di classificazione durante transizioni posturali, lavori domestici e movimenti generici effettuati stando in piedi ma diversi dal camminare o correre. Questo rapporto é stato interpretato osservando per prima cosa la relazione inversa tra attività a bassa intensità e occupazioni sedentarie e successivamente l'influenza della durata di occupazioni sedentarie nell'aumentare la concentrazione sanguigna di insulina. Ció ha portato a concludere che effettuare attività a bassa intensità puo' offrire protezione contro malattie cardiovascolari, per via della diminuzione della concentrazione di insulina e del relativo aumento del controllo cardiaco autonomo (**Capitolo 7**).

In conclusione, il riconoscimento automatico dell'attività fisica é stato ottenuto con successo, utilizzando il segnale misurato con un accelerometero triassiale ed un algoritmo di classificazione ad albero. Sebbene Tracmor$_D$ si é dimostrato uno strumento valido per predirre la spesa energetica giornaliera, il riconoscimento dei tipi di attività fisica ne ha migliorato la stima, evitando il problema inerente alla relazione tra *activity counts* ed AEE per diversi tipi di attività. Inoltre, questo nuovo approccio ha portato alla definizione di quali modificazioni nell'attività abitudinaria comportano un incremento della spesa energetica. Per finire, il riconoscimento dell'attività fisica é stato usato per definire la relazione esistente tra i tipi di azioni compiute giornalmente e indici della variabilità cardiaca, rilevanti come indicatori del rischio per malattie cardiovascolari. Futuri progressi tecnologici per sensori di accelerazione e l'uso di algoritmi di riconoscimento dell'attività fisica, potranno giocare un ruolo chiave nella definizione di interventi per la promozione della salute, basati su prescrizione dell'attività fisica incentrati sulla risposta fisiologica desiderata.

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About the author

Alberto G. Bonomi was born in Casorate Primo (Pavia, Italy) the 19th of October 1981. At the age of 19 he started his academic career at the Politecnico University in Milan. In 2003 he received a Bachelor's degree in biomedical engineering. In 2006, he graduated as a M.Sc. in biomedical engineering with a thesis on non-invasive assessment of early lung edema formation using near-infrared spectroscopy. During the first half of 2006, he worked as a graduate research assistant at the Biochemistry Department of the McGill University in Montreal (Canada) broadening his knowledge in optics, optoelectronics and multi-parametric modeling. In September 2006, he obtained a scholarship for a PhD position at the Maastricht University, granted by Philips Research Laboratories. At the same time, he joined the group Care and Health Applications at Philips Research where he investigated measurements of human physical activity and non-invasive biomarkers of metabolic health. In September 2010, he assumed the position of research scientist in the group Medical Signal Processing at Philips Research Laboratories working towards the development of advanced systems for the management of heart failure. His research interests include the development and validation of wearable sensors and computational models for diseases prevention and management.

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