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13. ABSTRACT (Maximum 200 Words)
The announcement of the Research Program in Technologies for Metabolic Monitoring (DAMD17-BAA-TMM02) called for "new, novel and unconventional approaches to the field of metabolic monitoring." Given the significance of physical activity and energy expenditure (EE) to health for both military and civilian populations, we proposed a feasibility study to achieve the following goals: 1) to develop and validate non-invasive portable techniques in monitoring detailed physical activity and accurately predict EE, and 2) to determine specific physical training related energy costs and physiological responses in ROTC cadets. The specific tasks are: 1) To measuring physical activity and EE under laboratory conditions. 2) To develop accurate EE prediction models. 3) To measure energy demands during field training in ROTC cadets. 4) To perform nutritional and fitness assessments. We have designed a two-stage data collection periods, expanding one academic year (Fall-Spring). Despite several delays, we initiated the studies in September 2003. Up-to-date, we have collected 58, 83, and 100% data for tasks 1,3 and 4, respectively, for the 1st stage assessments. We will complete this stage at the end of November 2003 and the data processing for task 2 will be performed. Phase 2 of the study is being planned.

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INTRODUCTION

This proposed study was in response to the specific call from the US Army Medical Research and Materiel Command (MRMC) for Technology of Metabolic Monitoring program (**DAMD-BAA-TMM02**), in which research projects were solicited to "*identify and assess technologies that can improve our ability to collect and interpret metabolic data ... and to use that data to extend our understanding of human metabolism in healthy, diseased, and stressed states*". The predominant contributor to a person's energy metabolism is physical activity. However, current knowledge in physical activity and its contribution to the health and diseases of humans is limited. This is mostly due to limited technology in accurate and detail measurements of the highly variable nature of human physical activity and its related energy expenditure (EE). Our research expertise and environment position us in an inimitable position for developing and validating portable devices for EE measurement in humans. In this study, we propose to develop a **novel** and **non-invasive** approach to accurately determining the detailed metabolic demands in ROTC cadets during physical training (PT). This study will establish close collaborations between clinical researchers and biomedical engineers in advancing the technologies of portable metabolic monitoring, which are essential in determining the inner relationships between energy balance and health for military personnel (Fridel et. al, 1997) as well as the general public. Working in close collaboration with the Vanderbilt University Army ROTC program, we will further investigate the physiological demands during PT, while setting long-term goals to optimize soldiers' health, fitness, and conditionings.

BODY

The approved specific tasks for this project are: 1) ascertain simultaneous physical movement data from a new activity/posture monitor and EE data from our room calorimeter; 2) establish accurate models of prediction EE from the body motion parameters; 3) validate the accuracy and reproducibility of the models with gold-standard techniques under field conditions; and 4) assess nutritional, fitness, and other physiological measures prospectively. We are approved to study 12 Vanderbilt ROTC cadets. The approved schedule is as the following:
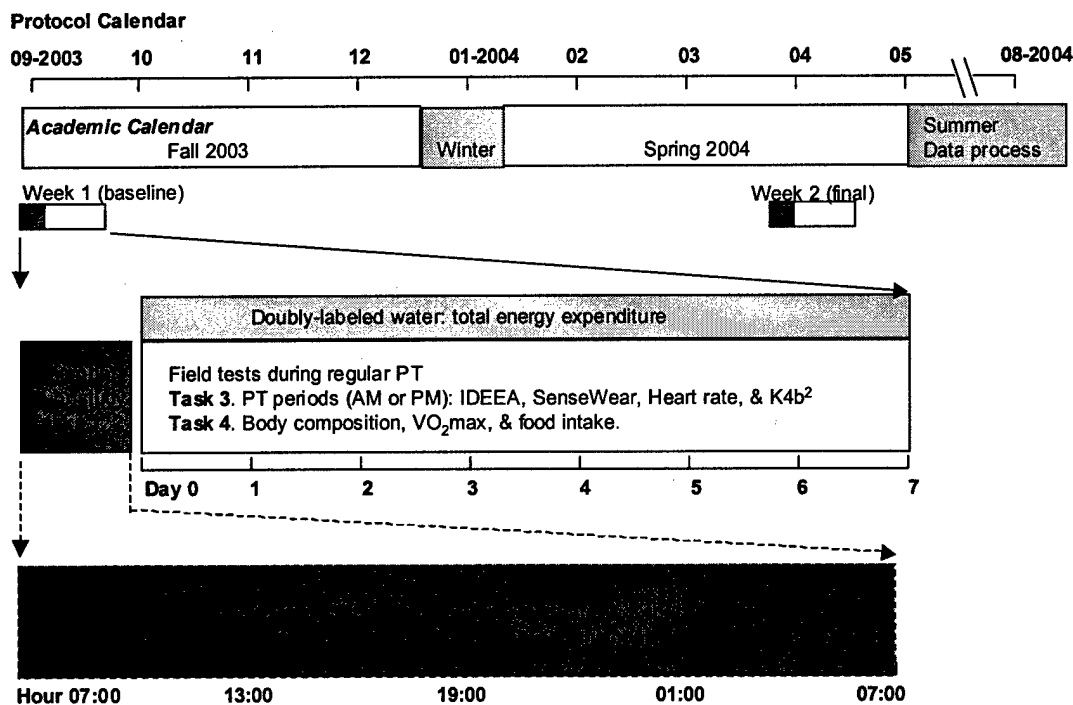

Figure 1. Approved study design and timeline.

Accomplishments to date:

Pre-testing: we have successfully recruited 12 cadets (10 males and 2 females; 8 Caucasians, 2 African-American, 1 Asian, and 1 other). The general characteristics are:

	Mean ± SD	Range
Body mass (kg)	79.2 ± 13.8	60.3 – 100.0
Height (cm)	176.4 ± 8.23	158.0 – 188.0
Age (yrs)	19.8 ± 1.0	18 – 21
BMI (kg · m^{-2})	25.3 ± 3.4	20.2 – 30.2

We received the Surgeon General's Army Human Subjects Research Review Board (HSRRB) approval in July 10th, 2003.

Task 1: For week 1 (1st of the two phases), we have collected seven 24-hour period data, with all five others schedule to complete by November 23rd, 2003. There were no adverse events during these testings.

Task 2: We will proceed with data processing as soon as we finished the five collections from Task 1. This is to minimize processing bias and errors while improving efficiency.

Task 3: We have attempted field data acquisition in 11 of the 12 recruited cadets, complete data was collected in eight of the 11 trials. We are currently pre-processing such data.

Task 4: We have measured body composition in 11/12 cadets, and in all 12 for fitness levels (VO$_2$max) and food intake. The results of the body composition and fitness levels are as follow:

	Mean ± SD	Range
Body Composition (%fat)	17.5 ± 7.2	7.1 – 31.2
VO$_2$max (ml O2 / kg · min)	53.8 ± 8.0	43.0 – 69.5

Problems encountered:

Pre-testing:

Delay of testing cycle: due to the actual funding did not start until October 2002, our original proposed testing cycle (with academic year) had to be change to 1 year later. This was approved.

Acquiring doubly-labeled water (DLW): although we started the process of finding suppliers immediately after we received grant approval, we were only able to get enough isotopes for 12 cadets in October 2003. We then change the original design of validation from using the DLW for both Phases to only the final Phase, and received approval.

Task 3:
Since our test instruments are not waterproof, several of all field trials were proponed due to weather.

Our original proposal of field trials was designed to be conducted in the afternoon PT sessions. However, starting the Fall 2003 semester, all Vanderbilt Army ROTC PT has been changed to 0600 AM. Since it takes about 20 minutes to equip a test subject with all the test instruments, the demands on testing cadets to be in the field about 1 hour earlier (3-4 trials conducted simultaneously, as approved) has been somewhat challenging. We have also encountered some incomplete collections (3 from the K4b^2, 1 from the IDEEA, and 4 from the

heart rate monitors) during these field trials, of which some were due to operational errors in the darkness, and others were due to equipment failure. We are researching potential improvements to decrease errors in our future field trials for Phase 2.

Key Research Accomplishments

- Technical improvements in physical activity monitoring devices.
- Development of advanced analytical modeling techniques.

Reportable Outcomes

1. During the last funding period, the PI was invited to present in the Metabolic Monitoring Technologies for Military Field Applications. Committee on Military Nutrition Research Food and Nutrition Board. Institute of Medicine, the National Academies, Jan 8-9, 2003. (With an invited manuscript to the IOM report, please see Appendix I).

2. The PI also submitted a manuscript (using previously collected data) to the Diabetes Technology & Therapy in March 2003, which will be published in the December 2003 issue in the Military Metabolic Monitoring Section (please see Appendix II).

Conclusions

- This study should initiate the crucial steps towards fundamental changes in the development of field techniques to accurately measure detailed physical activity and EE_{ACT}.
- The results of this research should also lead to larger studies to better evaluate the physical and physiological demands involved in physical trainings in military personnel.
- The applications of these devices in the field need further modifications.

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TITLE

The use of portable accelerometers in predicting activity energy expenditure

Kong Y. Chen

For

Metabolic Monitoring Technologies for Military Field Applications

Committee on Military Nutrition Research

Food and Nutrition Board, Institute of Medicine, The National Academies.

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INTRODUCTION

"A soldier's level of physical fitness has a direct impact on his combat readiness" (US Army, 1998). The balance of energy intake (EI) and energy expenditure (EE) can significantly affect soldiers' physical fitness, conditioning, and overall health. The predominant contributor to the variations of EE is physical activity. Unlike most civilian populations, soldiers often are subjected to extreme negative energy balance (EE far exceeds EI) (Fridel et. al, 1997). In order to achieve optimum energy balance, accurate and detailed measurements of both EI and EE are crucial. However, our current techniques in assessing physical activity are limited, such that possible associations between physical activity and the related EE (EE_{ACT}) with respect to the health and performance in military personnel have not been well determined.

Daily EE can be categorized into three major components: basal or resting EE (also called basal metabolic rate, or BMR), thermic effect of food (or food-induced thermogenesis), and EE_{ACT}. Resting EE is the rate of EE measured in postabsorptive, well rested, and thermoneutral conditions. In sedentary subjects, resting EE is the major component of EE (Flatt 1978). Inter-individual variations in resting EE of normal humans can be explained by differences in fat-free mass (the primary contributor), age, sex, familial traits, and fat mass (Ravussin et. al, 1986, 1987). Thermic effect of food represents the increase in EE following meal ingestion for absorbing, processing, and storing the nutrients. There are two recognized subcomponents, obligatory and facultative thermogenesis, which combine to represent a small component to total EE (<8-10%) (Jéquier et. al,1988 and Wells et. al, 1981). EE_{ACT} is the largest variability to total EE in humans. Moderate walking can increase EE by 3 times, while a more vigorous activity such as running can elevate EE by 10 times. Compared to civilians who generally have more sedentary lifestyles, EE_{ACT} is particularly important in soldiers' nutritional

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and physiological state, affecting performance and overall health (DeLany et. al, 1989 and

Burstein et. al, 1996).

MATERIAL AND METHODS

Measuring energy expenditure

Doubly Labeled Water (DLW) is considered as the "gold standard" for measuring EE in

the field or free-living conditions. It determines the net disappearance of hydrogen (in water) and

oxygen (in water and carbon dioxide) by labeling them with stable isotopes $^2H_2^{18}O$ (Schoeller, et.

al, 1982, 1996). The major advantage of the DLW is its non-invasiveness and non-intrusiveness.

It has been used to assess EE of soldiers in the field and the impact of different rations (DeLany

1989), climates (Burstein 1996), and other training conditions (Forbes-Ewan et. al, 1989).

However, the main limitation of DLW is that it measures total EE during a period of 7-14 days,

without being able to detect the type, duration, and intensity of physical activity, or to trace

variations in physical activity and related EE within certain periods. Furthermore, the high cost

and relative limited availability of ^{18}O make this method difficult to apply.

Indirect calorimetry is the "gold standard" method of measuring resting EE, thermic

effect of food, and EE_{ACT} under controlled or laboratory environments. It uses a facemask, a

ventilated hood, or a respiratory chamber (Sun et. al, 1994), to measure oxygen consumption and

carbon dioxide production non-invasively. Major advantages of indirect calorimetry are the

immediate and detailed measurements of the rates of EE and nutrient oxidation. The major

disadvantage is the limited application under free-living conditions.

Methods of assessing physical activity

Studying the relationship between physical activity and health is complicated by the

variable nature of physical activity. A particularly challenging area has been the development

and application of accurate, valid, and cost-effective techniques to quantify physical activity under field conditions (Wilson et. al, 1986, Paffenbarger et. al, 1993, and Washburn et. al. 1986). Numerous methods have been utilized to measure EE during physical activities. They vary greatly in their usefulness in different study populations and designs (Shultz et. al, 2001). They can generally be categorized as subjective and objective methods.

Subjective methods include the use of direct observations, physical activity records, and survey and recall questionnaires. These techniques are used for various time periods and settings. Although inexpensive and easy to implement, their accuracies are severely limited by the recording, recall, interviewer, and other biases. Results from most subjective physical activity monitoring methods are also difficult to quantify and to compare inter-individually. Predictions of EE_{ACT} using these methods could be further flawed by interpretation and translation errors.

Objective methods for current measurements of physical activity mainly consist of mechanical/electronic devices. Since walking and running are the most common types of physical activities, *step counters* are often used estimate overall activity levels. Several types of step counters exist, including pedometers using a mechanical movement counter (Bassey et. al, 1987 and Washburn et. al, 1980), mercury switches (Cauley et. al, 1987), and electronic load transducers and foot contact monitors inserted into the heels of shoes sensing loads held, lifted, or carried, and walking activity (Barber et. al, 1973, Dion et. al, 1982, Hoyt et. al, 1994, and Weyand et. al, 2001). These are generally simple, small, and relatively inexpensive devices that are based on the principle that EE_{ACT} is correlated with individual step frequency and foot contact times (Kram et. al, 1990). The main limitation is that the sensitivity and accuracy of step counting may vary significantly among activity types inter- and intra-individually. Furthermore, stride lengths, a crucial element of the velocity and distance traveled, are usually estimated.

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Researchers have recently focused on an array of new activity monitors based on *accelerometers*, which directly measure body movements in terms of acceleration. The most currently used accelerometers are piezoelectric sensors that detect accelerations in one (typically vertical direction) or in three orthogonal planes (anterior-posterior, lateral, and vertical). Results can be recorded in a microcomputer. Most current marketed monitors are usually placed on the hip or waist (for its closeness to the center of body mass), although ankle or wrist monitors are also used. Caltrac, Tritrac-R3D (both by Hemokinetics, Madison WI), RT3 (Stayhealthy, Monrovia CA), Computer Science and Application (CSA, Shalimar FL), Tracmor (Maastricht, The Netherlands), and ActiWatch (Minimitter, Sunriver OR) are just a few examples of marketed systems. In several validation studies using these monitors, correlation values ranged from 0.65 to 0.92 between EE measured by indirect calorimetry and accelerometer readings during various activities (Bray et. al, 1994, Bouten et. al, 1994, Chen, et. al, 1997, and Freedson et. al, 1998), where level walking showed the highest correlation with the waist worn triaxial accelerometers. The advantages of the accelerometry devices include their small size and most are wireless, non-invasiveness, and minimally intrusive to normal subject movements during daily activities. Additionally, they are easy to use for subjects and testers, detectable relative intensity, frequency, and duration, and the ability for extended measuring periods (minute-by-minute data for up to 28 days), thus making free-living monitoring more feasible. The major limitations include their inability to detect activity types for which the associations between measured acceleration and EE_{ACT} are dependent upon, single site monitoring that is unable to detect movements from other body segments, limited prediction algorithms to estimate EE_{ACT} across a wide range (Chen 1997), and inability to differentiate EE due to postural changes and other low intensity physical activities. To compensate for these errors, a combination of using

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accelerometry devices and inclinometer(s) or mercury switches was used to detect posture and motions were reported (Levine et. al, 2001 and Walker et. al, 1997). Recently, several research labs have reported the feasibility of using accelerometer arrays that were positioned at different body segments, mainly the chest and thighs, to monitor the types of activities by postural identifications (Fahrenberg et. al, 1997, Foerster et. al, 2000, Bussman et. al, 2001, Zhang et. al, 2003). However, EE_{ACT} predictions from these monitors have yet to be carefully validated.

Works from the Vanderbilt Energy Balance Lab

Equipped with the state-of-the-art *whole-room indirect calorimeter* at Vanderbilt, we are in a unique environment to develop and validate methods of EE_{ACT} predictions using portable activity monitors. The room calorimeter is a small, airtight environmental room (2.6x3.3x2.3 m^3, 19,500 liters in net volume), equipped with a desk, chair, outside window, toilet, sink, telephone, TV/VCR, audio system/alarm clock, and fold-down mattress to simulate free-living conditions (Figure 1). Oxygen consumption and carbon dioxide production are calculated by measuring the changes of oxygen and carbon dioxide content of the air inside the calorimeter and by the flow rate of the purged air times its concentration of gases. A special multi-channel air sampling system was designed to ensure an even sampling of the gas expired by the subject. Temperature, barometric pressure, and humidity of the room are precisely controlled and monitored. With these measures, the minute-by-minute EE is calculated with the highest precision reported (>90% with each minute and >99% over 24 hours) (Sun 1994).

RESULTS

In a previous study (Chen 1997), we used a hip-worn triaxial accelerometer monitor, the Tritrac-R3D Research Ergometer (Hemokinetics, Inc. Madison WI), to detect body motion during physical activities. A heterogeneous group of healthy adult volunteers (85 women and 40

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men) each spent two separate 24-hr periods (one day with non-intensive walking and stepping exercises and the other day without, respectively denoted exercise and normal days) in our room calorimeter, where each subject's minute-by-minute EE and body movements were measured simultaneously. The Tritrac-R3D's simple linear prediction model, using the combined signal from all three axes, significantly underestimated EE_{ACT} (by 33% and 49%) and total EE (by 17% and 26%) for normal and exercise days, respectively (Figure 2, parts A and B). Using the EE and acceleration data measured during the exercise day, body acceleration components (A) measured by the Tritrac-R3D were fitted into a non-linear two-parameter model:

$$EE_{ACT} = a \; x \; A_{horizontal}^{\;p1} + b \; x \; A_{vertical}^{\;p2},$$

where coefficients $a, b, p1, and p2$ were determined by optimization with minimum prediction error for each study individual. Results showed significant improvements (all $P<0.001$) in modeling total EE_{ACT} (Figure 2, part C), standard error estimation parameters, and correlation coefficients. We then applied the developed models to the measured acceleration during the second 24-hr period (normal day) and demonstrate that the predicted EE_{ACT} were significantly ($P<0.001$) better than the Tritrac-R3D model in estimating EE_{ACT} and total EE (Figure 2, part D). Furthermore, we showed that a generalized model, using subject's gender, weight, height, and age to replace the individualized coefficients ($a, b, p1, and p2$ from the equation above, shown in Figure 2, parts C and D), was also superior to the one-parameter-linear model by Tritrac-R3D.

However, periods of EE_{ACT}, particularly of lower intensities, were still underestimated, potentially due to inadequate movement detections of the upper body motion. In a recent study, we used a similar study design and measured EE during a 24-hr period in the room calorimeter in 60 healthy volunteers. Body movements were simultaneously measured using the same Tritrac-R3D triaxial accelerometer (worn at the hip). We added a wrist accelerometer (ActiWatch64,

Minimitter, Sunriver OR) on the dominant arm for upper body movement measurements. The non-linear power-fitting model was then expanded to include the arm accelerations:

$$EE_{ACT} = a \: x \: A_{hip, horizontal}^{p1} + b \: x \: A_{hip, vertical}^{p2} + c \: x \: A_{arm}^{p3},$$

We found the Tritrac-R3D and the ActiWatch combined model accurately estimated EE_{ACT} in all intensity categories compared to measured EE_{ACT} by the calorimeter (Figure 3). The particular improvements were in the measurement of lower intensity physical activities, in which sedentary individuals tend to spend most of their time. A second 24-hour study was repeated in a subgroup of 12 volunteers and showed accurate EE_{ACT} prediction compare to measured values (Figure 4).

DISCUSSION AND CONCLUSIONS

In view of the number of current field techniques for measuring detailed physical activity, accelerometers have been shown to be valid and useful. However, the applications of portable monitors to accurately predict energy demands in military personnel during training and field operations are unique. Compared to the more sedentary civilian populations for whom the most current activity monitors are designed, soldiers participate in routine training regiments that are often subject to increased physical demands. Marching and running with significant added loads (>10kg), crawling, jumping, climbing, and many other lifting or pulling activities are just a few of the activity types that will present challenges to existing technologies. Furthermore, many trainings and operations are conducted in extreme external environmental conditions, such as hot or cold climates (Burstein 1996), dry desert or humid jungles (Forbes-Ewan 1989), and high altitude (Hoyt et. al, 1994), while the internal stress from the imbalance of high total energy demands vs. low energy intake, sleep deprivation, fatigue, and psychological stress (Nindl et. al, 2002 and Troumbley et. al, 1990) may further exacerbate the complexity of the physical activity and EE_{ACT} estimations. Thus, we need to develop and optimize more specific portable methods

for the measurements of the various activity types, intensities, durations, and frequencies, and extend to the associated energy demands in military personnel during sustained field operations. Two general areas of improvement are: sensor technologies and model development.

Current marketed accelerometry activity monitors primarily use the piezoresistive sensors, either stand-alone or build in the surface-mounted and integrated chips. Although mostly unpublished, the ranges of acceleration are generally 0.05-1.0 g, with resolution of 0.02 or worse, and sampling rates of 32 Hz or lower. Although this may be sufficient for monitoring majority of the physical movements of the center of mass (e.g., for the hip-worn units), movements of upper extremities can have higher frequency components and may exceed the maximum range in short bursts. These limitations would introduce inaccuracies in measurements. Most current activity monitors only use the dynamic component (or the AC component) of the raw signals from the sensors, partially due to the fact that the baseline (or the static or DC component) of piezoelectric sensors drifts with temperature and directional changes. However, if the sensor(s) are positioned at proper locations, such as the chest, it may be useful to access such baseline change with respect to sensor direction for assessing body postures, which may indicate the type of the activities. The dynamic signal from the sensor is generally filtered (corrected for baseline drifts), digitized, full-wave rectified (turn the negative values to positive), and integrated to 15-second epoch or longer to yield the output of activity counts. Although most of the current accelerometry monitors are packaged for easy operations for field researchers, almost all current marketed monitors do not allow user to change key parameters such as sampling rate or to collect raw signals, which are crucial to improve signal ranges and enables model improvements.

Since current available monitors have limited ability to detect wide ranges of physical activity types and intensities, the modeling of the acceleration output to predict EE_{ACT} is an area

that needs much more development. We have demonstrated that the acceleration components recorded in the separate directions can be weighed differently to enhance EE_{ACT} prediction, due to body movements in the vertical axis normally demand more energy due to the increased work against gravity, such as in the cases of weight-bearing activities walking, running, and stepping (Haymes et. al. 1993 and Wong et. al. 1981). Thus, the weighing of the contributions in EE_{ACT} prediction models should reflect such differences. Furthermore, the linear relationship between the acceleration and EE_{ACT} may not be the pertinent model for all activity types and intensities. We have demonstrated the development and the validations of a relatively simple power prediction model that significantly improved the EE_{ACT} estimation from a linear model.

The placement of the monitor is also important. Previous studies have confirmed that the center of mass (near waist level) is the ideal site for monitoring, particularly for weight-bearing activities that contribute to the largest dynamic changes in energy cost. From our unpublished data, we have also seen that minute-to-minute EE during a 24-hr period correlated significantly better with raw measurements of physical activity by a hip-worn triaxial accelerometer (R=0.825±0.046) than with a wrist-worn uniaxial accelerometer (0.646±0.093, P<0.001, N=60). However, previous studies also illustrated that a single hip-worn monitor would be inadequate in measuring various physical activity types and intensities. Therefore, combination models that combine signals from multiple body segments need to be explored for improved accuracy in predicting EE_{ACT}.

In addition, other assessment techniques involve physiological measurements may also be incorporated with simultaneous accelerometry monitoring to further improve EE_{ACT} modeling. An example is the use of heart rate monitors. They present a simple and objective method for the estimation of EE during certain levels of physical activity and exercise (Spurr et.

al, 1986). Moreover, heart rate monitoring may facilitate the measurements on fatigue, state of hydration, body temperature changes, and emotional state (stress) that could affect the energy metabolism (Yoshida et. al, 1994 and Nielsen et. al, 1993). Other physiological parameters, such as core body temperature (Gass et. al, 1998 and van Marken et. al, 2001), galvanic skin conductance (estimating heat loss through sweating), and surface electromyography (measures of muscular activity), may also be explored to optimize the prediction of EE_{ACT}.

In summary, to enhance our abilities to assess the energy demands in soldiers in the field, future research in technologies should focus on small and wireless sensors that can be positioned non-invasively and non-intrusively to measure body movements as well as physiological responses. Accelerometers are suitable for many aspects of the physical activity monitoring; however, much can be improved to increase their sensitivity and further reduce their size. The complex nature of the human physical activity patterns, large inter- and intra-individual differences in energetic efficiencies, and inherent limitations of the sensors, dictates that the development of models to accurately predict EE_{ACT} should integrate more unique features of the signals from the sensors. This requires that we collect the raw signals from sensors. Moreover, advanced pattern recognition and automated classification modeling techniques, such as artificial neural networks that can incorporate multiple input parameters and output feedbacks for non-linear and adaptive modeling, need to be explored. The ideal development processes of such portable activity monitors should include the use of a respiratory chamber for sensor and model explorations under laboratory conditions, portable indirect calorimeter units for short-term field evaluations, and DLW for overall validations. Furthermore, we should optimize such monitoring systems to the specific applications through modeling, such as weather conditions and external loads, while broadening the general applications to civilian medical research.

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Figure legends

Figure 1.   The whole-room indirect calorimeter at Vanderbilt University.

Figure 2.   Total daily energy expenditure (TEE) estimated by the Tritrac-R3D model (**A.** Exercise Day, and **B.** Normal Day) in 85 healthy women and 40 men, and by the two-component nonlinear models (**C.** Exercise Day, and **D.** Normal Day) versus TEE measured by the calorimeter. The line of identity signifies a perfect match between the estimated and the measured values in the room calorimeter. In **C** and **D**, individual (Ind.) model represents the parameters fitted for each volunteer (from **A** and **B**), and general (Gen.) model represents the model using only the subject's gender, weight, height, and age to replace the individualized coefficients.

Figure 3.   Averaged energy expenditure (EE) in separate intensity categories of one 24-hour period in 60 healthy sedentary women (age 35.4 ± 9.0 years and BMI 30.0 ± 5.9 kg/m^2). Comparison between EE measured in the whole-room indirect calorimeter, estimated by the ActiWatch, the Tritrac-R3D, and the ActiWatch and Tritrac-R3D monitors combined. METs: metabolic equivalents, calculated as ratio of individual energy expenditure and resting energy expenditure. (* $P<0.05$ compared to the measured values).

Figure 4.   Total energy expenditure of physical activity (EE_{ACT}) in 12 healthy women during two 24-hr periods (identical protocol) measured in the room calorimeter, compared to the estimated from the activity monitors. One day was randomly selected for fitting with combinations of ActiWatch on the wrist of the dominant hand and Tritrac-R3D at the waist, and the second day used as prediction validation.
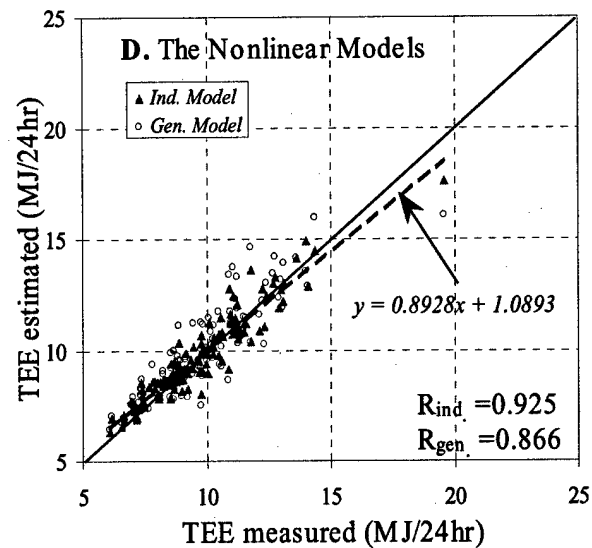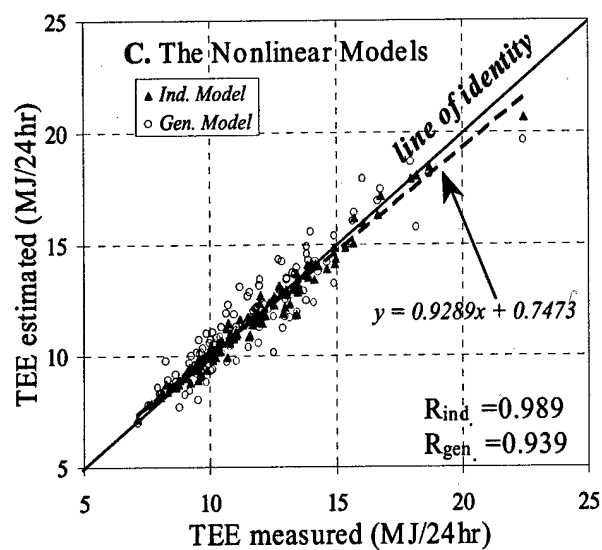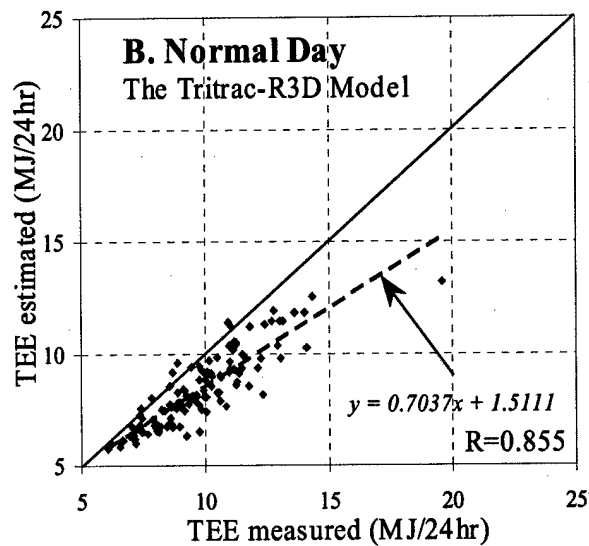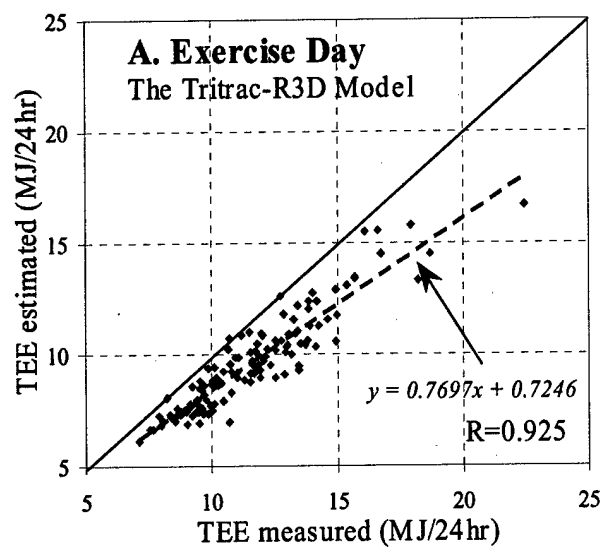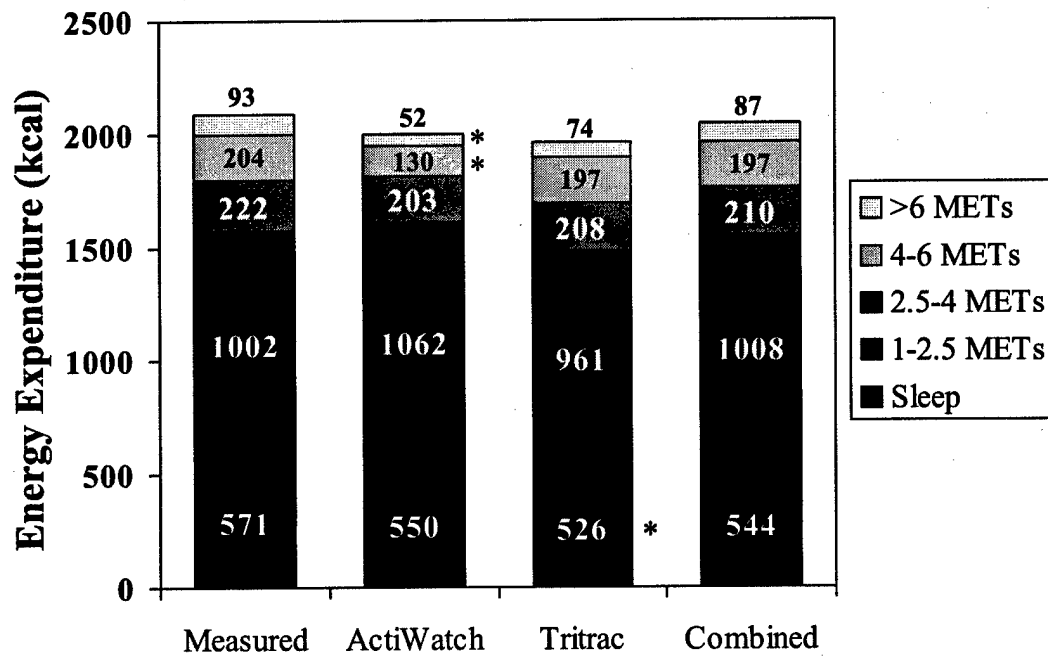
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Figure 1.
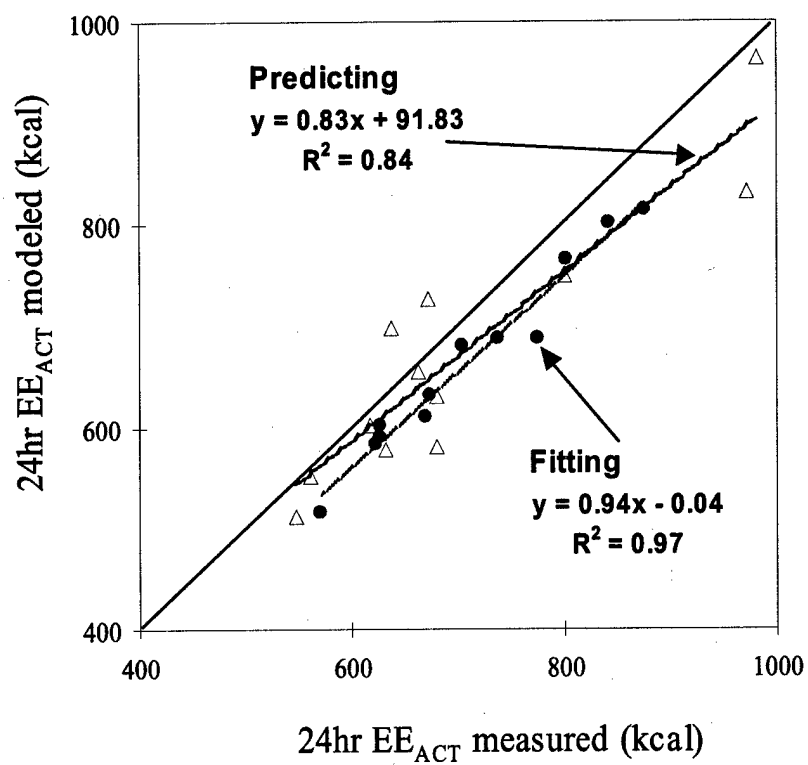
Figure 2.

Figure 3.

Figure 4.

Military Metabolic Monitoring

Predicting Energy Expenditure of Physical Activity Using Hip- and Wrist-Worn Accelerometers

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ABSTRACT

To investigate the association between physical activity and health, we need accurate and detailed free-living physical activity measurements. The determination of energy expenditure of activity (EE_{ACT}) may also be useful in the treatment and maintenance of nutritional diseases such as diabetes mellitus. Minute-to-minute energy expenditure during a 24-h period was measured in 60 sedentary normal female volunteers (35.4 ± 9.0 years, body mass index 30.0 ± 5.9 kg/m^2), using a state-of-the-art whole-room indirect calorimeter. The activities ranged from sedentary deskwork to walking and stepping at different intensities. Body movements were simultaneously measured using a hip-worn triaxial accelerometer (Tritrac-R3D, Hemokentics, Inc., Madison, Wisconsin) and a wrist-worn uniaxial accelerometer (ActiWatch AW64, MiniMitter Co., Sunriver, Oregon) on the dominant arm. Movement data from the accelerometers were used to develop nonlinear prediction models (separately and combined) to estimate EE_{ACT} and compared for accuracy. In a subgroup ($n = 12$), a second 24-h study period was repeated for cross-validation of the combined model. The combined model, using Tritrac-R3D and ActiWatch, accurately estimated total EE_{ACT} (97.7 ± 3.2% of the measured values, $p = 0.781$), as compared with using ActiWatch (86.0 ± 4.7%, $p < 0.001$) or Tritrac-R3D (90.0 ± 4.6%, $p < 0.001$) alone. This model was also accurate for all intensity categories during various physical activities. The subgroup cross-validation also showed accurate and reproducible predictions by the combination model. In this study, we demonstrated that movement measured using accelerometers at the hip and wrist could be used to accurately predict EE_{ACT} of various types and intensity of activities. This concept can be extended to develop valid models for the accurate measurement of free-living energy metabolism in clinical populations.

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INTRODUCTION

PHYSICAL ACTIVITY has been known to be have beneficial effects on overall health, particularly in decreasing the incidence of morbidity/mortality associated with common chronic diseases such as coronary heart disease, hypertension, and type II diabetes.[1,2] However, little quantitative evidence has yielded causal relationships,[3,4] mostly because of the large individual and time variations in the characteristics of the parameters of activity and health, and the lack of ability to accurately quantify physical activity. For example, both observational studies and clinical trials in a variety of populations have supported the hypothesis that physical activity plays a significant role in the prevention and treatment of type II diabetes, but what is less clear is how much physical activity is needed.[5,6] Objective and accurate measurements of physical activity and energy expenditure (EE) are crucial in the treatment and maintenance of such chronic diseases.

EE of activity (EE_{ACT}) varies within and among individuals, and contributes the largest variability to total EE in humans.[7] This contribution has significant consequences on overall energy balance, which determines the long-term body weight outcome. The current standard in objective measuring methods for EE are doubly labeled water[8,9] and the—indirect calorimeter.[10,11] The doubly labeled water method provides a mean value of EE for the entire measurement period, usually around 10–14 days, and does not allow one to calculate the day-to-day variation in EE. The other disadvantages of the technique are its high cost and the limited availability of ^{18}O. The indirect calorimeter is the best method to measure the components of daily EE [resting EE (REE), thermic effect of food, and EE_{ACT}]. It is relatively simple, and can be used either with a ventilated hood system (for a resting subject) or in a respiratory chamber for a longer period of time.[12] A major advantage of indirect calorimetry is the immediate response of oxygen consumption. Another advantage of indirect calorimetry in comparison with other methods is the possibility of assessing nutrient oxidation rates. However, it can only measure EE accurately under laboratory conditions.

Portable accelerometers, developed to objectively measure body movements and record detailed data for an extensive period, have been adopted to assess physical activities and EE_{ACT}.[13–20] We previously showed that EE estimated by a hip-worn triaxial accelerometer (Tritrac-R3D, Hemokentics, Inc., Madison, WI) significantly underestimated EE_{ACT} as compared with EE_{ACT} measured by a whole-room indirect calorimeter.[15] We then developed and validated a nonlinear model that used the acceleration components from the Tritrac-R3D for the estimation of EE_{ACT}. Although the estimation was accurate for the group, individual variation in EE_{ACT} prediction still existed, potentially because of undetected upper body movements. Since small errors over time can be significantly contribute to overall energy balance, our mission is to minimize individual errors. Therefore, we hypothesize that by adding an upper-body acceleration component (measured by ActiWatch AW64, MiniMitter Co., Sunriver, OR) to our previous hip-worn accelerometer model, the overall estimation accuracy of EE_{ACT} would be improved, compared with using each individual monitor alone. This investigation was also to demonstrate the process of using a whole-room indirect calorimeter to develop subject-specific EE_{ACT} predictive equations from portable accelerometers in humans.

SUBJECTS AND METHODS

Subjects

The data were part of a prospective study looking at possible seasonal variations in physical activity in sedentary women. A group of normal healthy women ($n = 60$) of heterogeneous characteristics and sedentary by self-report was recruited from local areas. Signed informed consent approved by the Institutional Review Board at Vanderbilt University was obtained before their participation in the study. Women were eligible for participation if they were apparently healthy, with no evidence of past or present metabolic diseases (e.g., thyroid disorders and type II diabetes), were not pregnant as determined by a serum pregnancy test,

did not use drugs known to affect energy metabolism, were eating a balanced diet, and were non-smokers. All participants were studied between days 3 and 12 after the onset of menses (follicular phase) to eliminate the influence of menstrual function on energy expenditure.[21] Study participants were compensated for taking part in the study. During the 2 weeks prior to the study, all participants were encouraged to maintain their normal pattern of activity. To cross-validate the models developed from this study, a randomly selected subgroup of subjects was asked to volunteer to repeat the protocol under identical conditions within 4 days of the first study. Characteristics of all study participants are shown in Table 1.

Experimental procedures

All participants reported to the General Clinical Research Center (GCRC) after a 10-h overnight fast. The 24-h study protocol involved spontaneous daily activities and an exercise protocol that was similar to the manual work and leisure activities that participants would perform in daily life. Specifically, the exercise protocol consisted of three 10-min walking periods with average speeds of 0.6 m/s, 0.9 m/s, and 1.2 m/s across the room and three 10-min stepping periods with average speed of 12 steps/10 s, 18 steps/10 s, and 24 steps/min, respectively, all with at least 10-min resting periods between each exercise. During the walking and stepping segments, subjects followed the appropriate exercise cadence set by a metronome. The spontaneous physical activities included various types and intensities, such as sitting, TV viewing, deskwork, walking around the room, and even some voluntary

exercises using the provided treadmill and stepper. Meals designed by the registered dietitian to maintain approximate energy balance were prepared at the Vanderbilt University GCRC metabolic kitchen and provided to the subject at 8:30 a.m., 12:30 p.m., and 5:00 p.m. The participants were asked to go to bed from 9:30 p.m. until 6:00 a.m.

Measurement of physical activity. The Tritrac-R3D monitor (weighing 170 g and measuring $11.1 \times 6.7 \times 3.2$ cm) was placed in a nylon pouch secured to the belt at the waistline on the right hip to measure body acceleration in three dimensions (x or anteroposterior, y or vertical, and z or medial–lateral axis). The ActiWatch (weighing 17 g and measuring $2.8 \times 2.7 \times 1$ cm), a uniaxial accelerometer, was worn at the wrist of the dominant hand to assess arm movements. The ActiWatch was worn during the entire study period, while the Tritrac-R3D was not worn during sleep for better comfort. Both monitors were set to record data at 1-min intervals.

Measurement of EE. The rate of EE was measured minute-by-minute in a whole-room indirect calorimeter (Fig. 1), an airtight environmental room that is temperature and humidity controlled. To provide facilities for daily living and to bridge the difference between laboratory and free-living environments, the room is equipped with a desk, chair, outside window, toilet, sink, telephone, TV/VCR, audio system/alarm clock, and fold-down mattress. It has been validated as a highly accurate system for determining detailed EE and physical activity.[11,22] Oxygen consumption (V_O2) and car-

TABLE 1. SUBJECT PHYSICAL CHARACTERISTICS

	All (n = 60)		Subgroup (n = 12)	
	Mean ± SD	Range	Mean ± SD	Range
Body mass (kg)	70.7 ± 16.4	45.0–131.1	65.9 ± 9.4	54.4–83.5
Height (cm)	164.9 ± 7.3	151.0–184.0	164.9 ± 8.3	156.0–184.0
Age (yrs)	35.4 ± 9.0	20.0–52.0	27.6 ± 5.1[a]	22.0–38.0
BMI (kg m^{-2})	30.0 ± 5.9	16.7–47.0	24.2 ± 2.3	21.4–30.3

BMI, body mass index.
[a]Significantly different compared with the rest of the subjects ($n = 48$), $p = 0.004$.
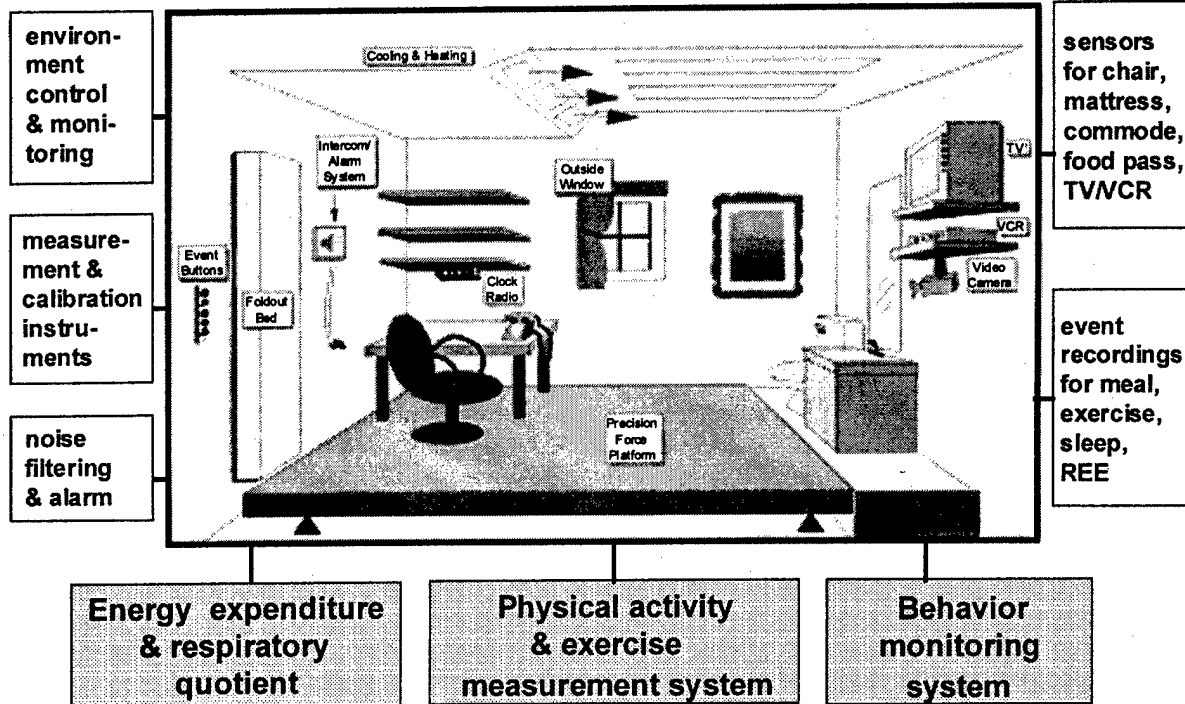
Whole-room Indirect Calorimeter

FIG. 1. Schematic diagram of the whole-room indirect calorimetry chamber at Vanderbilt University.

bon dioxide production ($V_{CO}2$) are used to calculate minute-by-minute EE with a system error of less than 1%.[11] This accuracy is critical for validation and model development of EE.

Anthropometry. Body weight was measured to the nearest 0.05 kg with a digital scale. Height was measured to the nearest 0.5 cm with a stadiometer.

Model development

The model development algorithm was similar to our previous studies.[15,16] The body accelerations ascertained from the Tritrac-R3D and the ActiWatch were used to fit the measured EE_{ACT} (EE − REE), first in separate models, and then combined in one model. REE was calculated during the 30-min resting supine posture while awake and immediately following overnight fasting and sleeping. A nonlinear model was previously proven to be superior compared with linear models,[7] and thus was also adopted for the current study. After

synchronizing the acceleration outputs with the measured EE, the acceleration counts from the Tritrac-R3D were stratified into the horizontal component (denoted H, where $H = \sqrt{x^2 + z^2}$), and the vertical component (denoted V, $V = y$). Each component was modeled by nonlinear power parameters to model individual EE_{ACT} as the following:

Tritrac-R3D: $E\hat{E}_{ACT}(k)$

$$= a \times H(k)^{p1} + b \times V(k)^{p2} \quad (1)$$

$$\text{ActiWatch: } E\hat{E}_{ACT}(k) = a \times AW(k)^{p} \quad (2)$$

Tritrac-R3D+ActiWatch: $E\hat{E}_{ACT}(k)$

$$= a \times H(k)^{p1} + b \times V(k)^{p2} + c \times AW(k)^{p3} \quad (3)$$

where $E\hat{E}_{ACT}(k)$ represents the estimated EE_{ACT} at the *k*th minute, and parameters such as *a*, *b*, *c*, *p*, *p*1, *p*2, and *p*3 were optimized to predict EE_{ACT} that had the best fit compared with the measured EE_{ACT}.

Statistical analysis

Descriptive data were expressed in mean ± 1 standard deviation (SD). Optimization was performed using the least sum of squared error algorithm with universal minimum. Correlation coefficient (Pearson's r) and standard errors of estimation (SEE) were used as the evaluation criteria:

$$SEE = SD(EE_{estimated} - EE_{measured}) \quad (4)$$

where $EE_{estimated}$ represents the estimated EE value by each model, and $EE_{measured}$ represents the EE measured by the indirect calorimeter for each study participant. The MATLAB software package (for Windows, version 6.1, Math-Works, Inc., Natick, MA) was used for the model development and evaluation of final predictions. Differences were compared by analysis of variance (ANOVA, Tukey's test) using SPSS for Windows (for Windows, version 11.0, SPSS, Inc., Chicago, IL); 95% confidence interval and $p < 0.05$ were used to identify statistical significance. Bland–Altman[23] plots, which express the difference with respect to the mean of the two measurements in a scatter graph, were used to explore differences between modeled and measured total EE_{ACT} across the study population.

To further evaluate the accuracy of the models for various activity intensities, the time periods of the study day were categorized according to the intensity. We stratified the non-sleeping activities into four categories: 1–2.5, 2.5–4.0, 4.0–6.0, and >6.0 times the REE (METs, including EE_{ACT} and REE), using measured EE as the standard. The estimated EE from the prediction models within the same time periods of these intensities was also categorized and compared with the measured EE using ANOVA.

RESULTS

Table 1 presents descriptive data for the 60 study participants and for the cross-validation subgroup ($n = 12$).

The 24-h EE was 2,132 ± 335 kcal, total EE_{ACT} was 821 ± 167 kcal, and REE was 1,403 ± 233 kcal for the entire group. Physical activity, measured in counts per minute for each individual by the Tritrac-R3D (vector magnitude) and ActiWatch, was significantly correlated with measured EE_{ACT} ($R = 0.825 \pm 0.046$ and 0.646 ± 0.093, respectively, $p < 0.001$). The estimated EE_{ACT} yielded from the predictive models (Eqs. 1–3) was significantly ($p < 0.001$) correlated with measured EE_{ACT}, and was higher ($p < 0.001$) than the correlation between the raw counts and measured EE_{ACT} (Table 2). However, compared with the EE_{ACT} measured in the room calorimeter, models using Acti-Watch (Eq. 2) and Tritrac-R3D (Eq. 1) individually significantly underestimated total EE_{ACT}: −113 (−189, −38) kcal ($p < 0.001$) and −85 (−161, −10) kcal ($p = 0.019$), respectively. The total EE_{ACT} predicted using the Tritrac+Acti-Watch model (Eq. 3) was not statistically different from the measured EE_{ACT}: −28 (−103, 48) kcal ($p = 0.781$). The degrees of agreement between estimated EE_{ACT} using each of these

TABLE 2. MINUTE-BY-MINUTE R AND SEE BETWEEN EE_{ACT} MEASURED BY THE INDIRECT CALORIMETER AND ESTIMATED BY THE MODELS

Model	R (estimated vs. measured EE)	SEE (kcal/min)
Tritrac-R3D (Eq. 1)		
Mean ± SD	0.90 ± 0.03	0.364 ± 0.088
Range	0.81–0.95	0.234–0.570
ActiWatch (Eq. 2)		
Mean ± SD	0.73 ± 0.08[a]	0.575 ± 0.142[a]
Range	0.53–0.90	0.356–0.862
Tritrac ± ActiWatch (Eq. 3)		
Mean ± SD	0.92 ± 0.03	0.334 ± 0.087
Range	0.81–0.96	0.212–0.546

[a]Significantly different from the Tritrac-R3D model and the Tritrac + ActiWatch model, all $p < 0.001$.

ActiWatch Model

$$y = -0.12x + 6.6$$
$$R^2 = 0.18$$

Tritrac-R3D Model

$$y = -0.03x - 91.5$$
$$R^2 = 0.02$$

Tritrac-R3D + ActiWatch Model

$$y = -0.05x + 9.8$$
$$R^2 = 0.08$$

Difference in total EE$_{ACT}$ (model estimated – measured) (kcal)

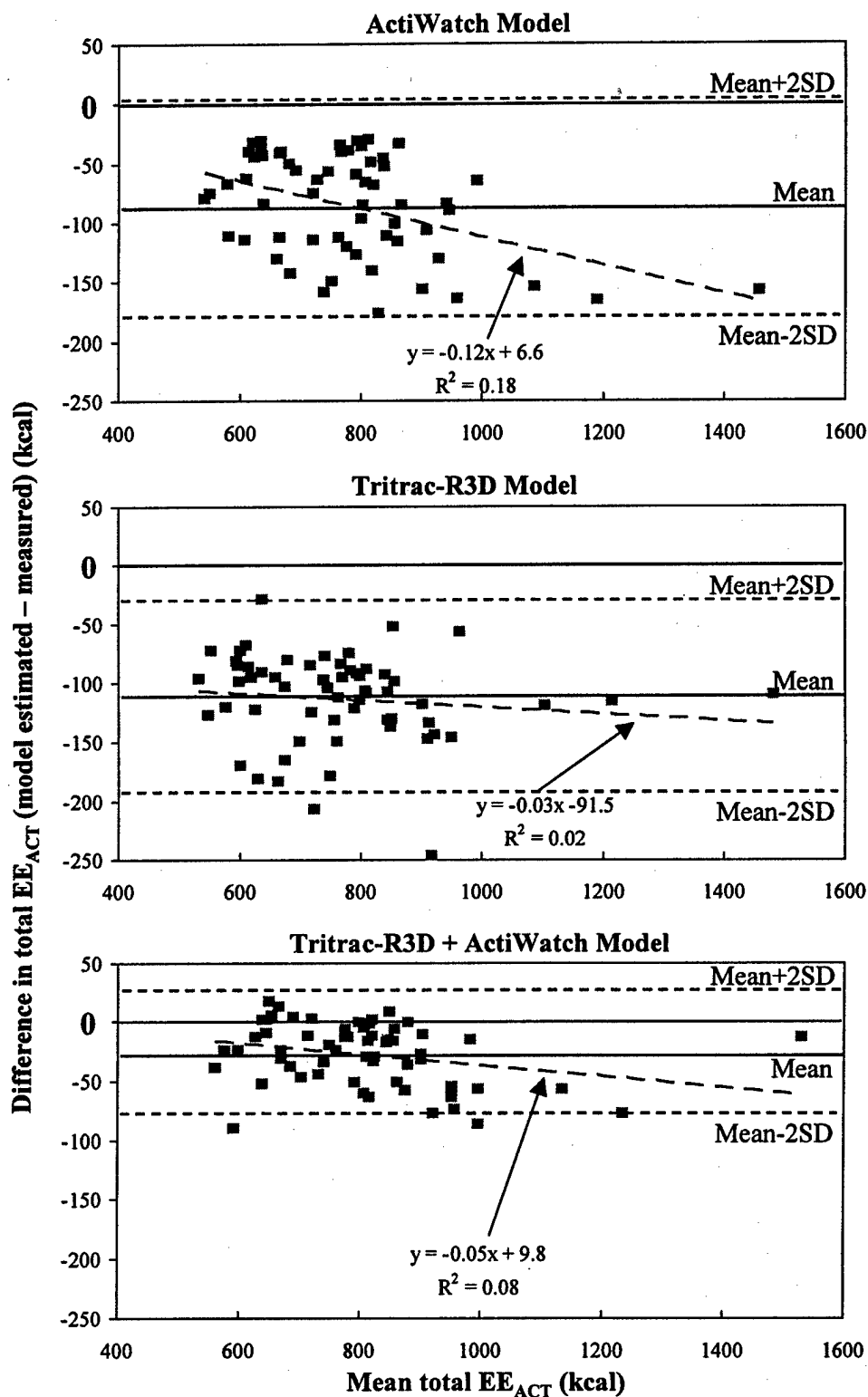Mean total EE$_{ACT}$ (kcal)

FIG. 2. Mean ± 2 SD of the difference between the measured (calorimeter) and estimated 24-h EE$_{ACT}$ using prediction models (ActiWatch, Tritrac-R3D, and Tritrac-R3D+ActiWatch, in Eqs. 2, 1, and 3, respectively), with respect to the mean of the EE$_{ACT}$ values.

three predictive models and EE_{ACT} measured in the room calorimeter are presented by the Bland–Altman plots in Figure 2. These plots show that the main differences among the three predictive models were the magnitude of mean error and the range of deviations in estimating total EE_{ACT}. This analysis demonstrates that the combination of two accelerometers improved both parameters over the two individual models.

Furthermore, both the Tritrac-R3D model (Eq. 1) and the Tritrac+ActiWatch model (Eq. 3) significantly (all $p < 0.001$) increased correlation coefficient (R) values and reduced SEE compared with the ActiWatch model (Eq. 2). The improvements from the Tritrac-R3D model to the combination model, although all in positive directions, did not reach statistical significance in terms of R ($p = 0.278$) or SEE ($p = 0.218$). The summary results of the fitting parameters of the models for Tritrac-R3D, Acti-Watch, and the two monitors combined (Eqs. 1–3) are summarized in Table 2. When compared among different intensity categories, we found the performance from the three predictive models varied (Fig. 3). The ActiWatch model underestimated the EE when intensity exceeded 4 METs ($p < 0.001$). Only the combination model was able to produce nonsignificant differences in EE_{ACT} values in all physical activity intensities.

In the smaller cross-validation subgroup, 12 subjects (characteristics summarized in Table 1) who repeated the 24-h measurements ex-

pended $2,008 \pm 260$ kcal/day and $2,000 \pm 295$ kcal/day for the first and second study day ($p = 0.840$), respectively. EE_{ACT} was also comparable between the two days (820 ± 199 kcal/day and 761 ± 201 kcal/day, $p = 0.763$). One of the two study days was selected randomly for model development. The fitting parameters in the combined model (Eq. 3) for each of these individuals were then applied to the acceleration output from the other study day, thus deriving the predicted EE_{ACT}. The comparison between the predicted and measured EE_{ACT} from the room calorimeter would then yield the cross-validity of the models. Total EE_{ACT} during the study period used for modeling was 710.4 ± 96.7 kcal and 665.2 ± 92.1 kcal for measured and fitted ($6.4 \pm 2.3\%$, $p = 0.014$), respectively. Total EE_{ACT} during the cross-validation study day was 724.5 ± 108.3 kcal and 684.2 ± 104.2 kcal for measured and predicted ($4.3 \pm 4.8\%$, $p = 0.140$), respectively. The scatter plot for the measured versus predicted EE_{ACT} (Fig. 4) further illustrates that the model appears stable and is able to accurately reproduce total EE_{ACT} for the majority of these subjects.

DISCUSSION

The need for accurate assessment of physical activity and its associated EE under free-living conditions is underscored by the rising toll of chronic diseases, such as obesity, type II dia-
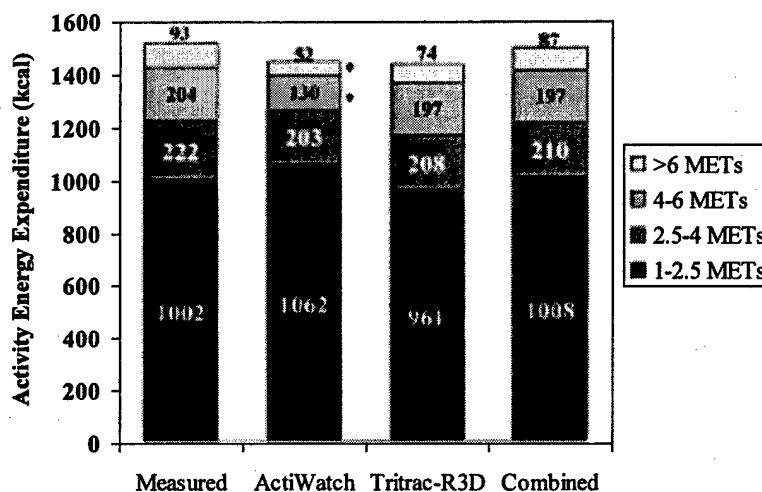

FIG. 3. Group mean EE_{ACT} in different intensity categories as measured by the calorimeter, modeled by the ActiWatch, Tritrac-R3D, and combined (Tritrac-R3D+Acti-Watch) models. $^*p < 0.05$ compared with the measured values.
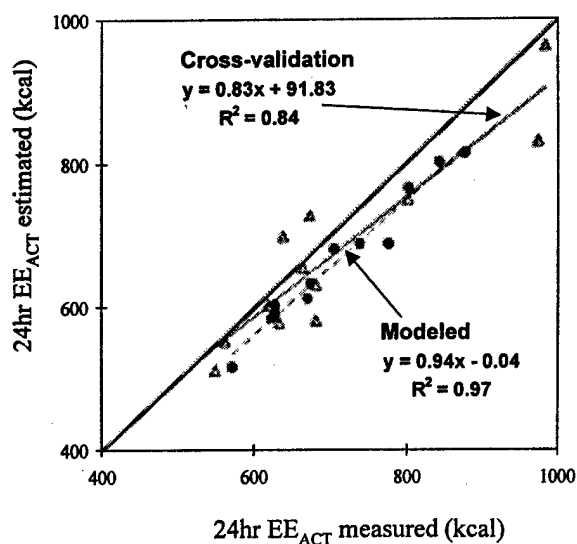
FIG. 4. Estimated total EE_{ACT} from the modeled day (dotted with dashed trend line) and the cross-validation day (triangle with solid trend line), versus the measured EE_{ACT} in the subgroup ($n = 12$). The line of identity is also shown for theoretical "perfect" fit.

betes, and cardiovascular disease. While considerable evidence supports a relationship between physical inactivity and type II diabetes,[5,6] the appropriate amount of physical activity needed to aid in the prevention or amelioration of this disease epidemic is somewhat speculative, largely because of the lack of accurate and validated methodology for measuring free-living physical activity and its associated EE. Portable accelerometers have been recognized as a reliable and objective technique for measuring physical activities under free-living conditions.[18,19] However, their ability to estimate EE_{ACT} has been an area that needs great improvement. Results of this study have shown that EE_{ACT} could be accurately assessed using these noninvasive movement monitors.

Estimation of EE by accelerometers has been studied under laboratory and free-living conditions. In earlier studies in which uniaxial accelerometers were attached at different anatomic sites, vertical acceleration at the hip had the highest correlation coefficient with measured EE during common activities such as walking and stepping.[13,24,25] Subsequent studies have demonstrated improvements of the EE–acceleration associations with three-dimen-

sional (triaxial) accelerometers in walking, running, and step exercise under laboratory conditions.[26,27] The current prediction models adopted by the Tritrac-R3D use the linear regression approach and only the vector magnitude of counts from all three axes. The performance of this model was shown to be acceptable for level walking and jogging (40–70% V_{O2max} on a treadmill) for a small group of young and fit individuals in one study,[28] but both overestimations[19,20,29,30] and underestimations[17,31] have been reported in walking and other free-living physical activities. Previously, we also found a significant underestimation of total EE_{ACT} by 50–70% using the Tritrac-R3D linear regression model.[15]

Furthermore, we developed an approach to model EE_{ACT} using a hip-worn triaxial accelerometer (Tritrac-R3D) by separating horizontal and vertical components and using a nonlinear power model to associate acceleration and EE_{ACT} over the broad intensity range of daily physical activities. Both approaches significantly ($p < 0.01$) improved the estimation accuracy of EE_{ACT}.[15,16] However, the Tritrac-R3D monitor was mainly sensitive to body movements at the center of mass, and thus could not adequately measure changes in EE due to physical activities performed by the upper body, which are a major part of many sedentary activities.

Swartz et al.[32] reported a bivariate regression model that combined hip and wrist acceleration data (uniaxial) and significantly improved prediction of EE in free-living physical activities. In our current study, we add a wrist-worn uniaxial accelerometer to our previously tested hip-worn triaxial accelerometer model, and further advanced this modeling concept using nonlinear modeling. One major advantage of this type of nonlinear modeling was that if a better fitting could be achieved with a linear model, then the power parameters (p values in Eqs. 1–3) would then be equal or very close to 1. In all three models, all power parameters were significantly less than 1 (all $p < 0.01$). This was in agreement with our previous findings.[15]

By comparing the results from different models, the estimated EE_{ACT} using Tritrac-R3D (Eq. 1) was significantly better than using ActiWatch (Eq. 2), in terms of SEE and R (Table

2). This indicated stronger associations between EE_{ACT} and the acceleration components measured at or close to the center of body mass rather than at the wrist, logically reflecting higher energy costs due to weight-bearing movements. Movements from the arm can often be quick even with little force exertion, thus leading to the slight overestimation of EE_{ACT} ($6.2 \pm 4.7\%$, $p = 0.121$) during low-intensity activities (1–2.5 METs) by the ActiWatch model (Fig. 3). In contrast, the ActiWatch model significantly underestimated EE_{ACT} during activities of higher intensity (>4.0 METs) because of less upper body motion during walking and stepping. The Tritrac-R3D model in Eq. 1 slightly underestimated the lower-intensity physical activities ($-4.3 \pm 6.9\%$ during 1–2.5 METs, $p = 0.459$), very likely because of the lack of signals picked up by the monitor during upper body movements, which was consistent with our previous study.[15] By adding the ActiWatch, the combination model slightly improved SEE and R values, compared with the Tritrac-R3D model (Table 2). Although neither achieved statistical significance, this model was the only one that showed nondifferential estimation of EE_{ACT} during all non-sleeping physical activity intensity categories. As a result, total EE_{ACT} was predicted most accurately by the combined model ($97.7 \pm 3.2\%$), compared with ActiWatch ($86.0 \pm 4.7\%$) and Tritrac-R3D ($90.0 \pm 4.6\%$) models. The contributions to the total estimated EE_{ACT} by the combination model were $67 \pm 23\%$ and $33 \pm 18\%$ from the acceleration components from the Tritrac-R3D and the ActiWatch, respectively. In line with our hypothesis, these findings collectively suggest that the combination model used Tritrac-R3D data for most of the weight-bearing activities when EE intensities were relatively high, and used the ActiWatch data for upper body activities during more sedentary activities when the intensities were lower.

This study had some limitations. First, it only included healthy normal adult females (11 African Americans, two Asian American, and 47 Caucasians), which may limit the generalizability of these model parameters. Unlike our previous study, we did not derive the generalized parameters for our models,

mainly because this was a fairly homogeneous population (middle-aged sedentary females) that lacked the spectrum of variations for generalization. However, the concept of using activity monitors to assess EE_{ACT} has been proven valid and feasible. Furthermore, we concentrated on a sedentary population with relatively high body mass index. This approach, however, allows us to establish a baseline for future studies on energy metabolism and physical activity in obesity and type II diabetes.

In conclusion, this investigation evaluated several EE_{ACT} prediction models using a hip-worn triaxial accelerometer (Tritrac-R3D) and a wrist-worn uniaxial accelerometer (ActiWatch) in a group of healthy women under close to free-living conditions in a whole-room indirect calorimeter. We found that a combined model using both monitors better estimated EE_{ACT} across all intensities compared with any single monitor model. In our study group, it has a 96.5% chance to detect total EE_{ACT} within ± 75 kcal, which may be clinically significant in exercise or diet prescription. This model was further validated for its predictive accuracy and stability in a subgroup. It is possible that the concept of developing predictive models for healthy individuals described in this study can be extended and validated in disease populations, such as type II diabetes. This may facilitate development of physical activity guidelines used as adjuvant therapy for the prevention and treatment of type II diabetes. Currently, we are using this approach to conduct a prospective study in assessing physical activity levels and EE in type II diabetic patients under various intensities of disease management protocols.

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