Multimodal Energy Expenditure Calculation for Pervasive Health: A Data Fusion Model using Wearable Sensors

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Abstract— **Accurate estimation of energy expenditure during exercise is important for professional athletes and casual users alike, for designing training programs and meeting their fitness goals. However, producing an accurate estimate in a mobile, wearable health-monitoring system is challenging because most calculations require knowledge of the subject's movement speed. Though determining precise movement speed is trivial on a treadmill, inaccuracies of the sensors in a mobile system have a negative impact on the accuracy of the final energy expenditure estimate. In this paper, we propose a novel method to calculate energy expenditure using sensor fusion, in which data from multiple sensors is combined to formulate the result, based on a linear-regression model. We combine data from our wearable system with embedded pulse sensor and pedometer to produce an estimate that is far more accurate than possible with the pedometer alone, reducing our mean-absolute error by 64.3%. These results indicate that it is possible to obtain an accurate energy expenditure estimate in a multi-sensor system, even with affordable, low-cost, and pervasive components that may not be accurate individually.**

I. INTRODUCTION

Monitoring energy-expenditure during exercise can be useful for anyone seeking to improve their fitness level, from casual users to professional athletes with strict training regimens [1]. Recent advances in technology have led to various wearable health-monitoring systems [2] capable of reporting energy expenditure and transmitting data wirelessly to a base station for real-time monitoring of energy expenditure at low costs. However, deriving energy expenditure from low-cost wearable sensors comes at the cost of accuracy.

Current methods to compute energy expenditure in a pervasive environment heavily rely on accelerometer based pedometers such as FitBit [3],[4]. Such techniques utilize the number of steps taken in order to compute the approximate speed of the user's movement and further estimate the energy expenditure. In other words, the computed energy expenditure is estimated using a single dimension of the user's activity: the number of steps. Moreover, determining the movement speed of a subject is dependent on the accuracy of the individual sensors, as well as the signal processing algorithms necessary to convert the raw data into the number of steps. Consequently, such technologies often provide inaccurate energy expenditure estimates. Moreover simultaneous monitoring of more than one user is rarely available for applications such as athlete monitoring systems.

Fig. 1. Initial prototype of the health-monitoring system

In this paper, we introduce a light-weight and inexpensive wearable sensor and an efficient computational method that improve the accuracy of the energy expenditure estimation in remote environment. The wearable sensory device is illustrated in Fig. 1.

The proposed method utilizes both an accelerometer and a pulse sensor, which are the two most important physiological signals in estimating the energy expenditure [5]. These two signals are combined using a sensor fusion technique based on a linear regression model. The accuracy of the proposed system is validated through a controlled experiment.

The system consists of a structure in which the wearable device transmits the captured data to a single aggregator (i.e. a mobile device). The system design specifically considers scalability of the system to be used on more than one user. In this case, the aggregator collects the data from all deployed sensors within 300-ft of range.

The rest of this paper is organized as follows. In Section II, related works are discussed. Section III provides an overview of the proposed pervasive system, and Section IV discusses the metric that processes the captured signals to estimate the energy expenditure. In Section V, detailed information about the experiment is discussed, and the results are provided in Section VI. Finally, concluding remarks are provided in Section VII.

II. RELATED WORK

This section provides an overview of existing wireless monitoring systems, as well as different methods for

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estimating energy expenditure. Energy consumption of a person during exercise is best quantified by METs (i.e. Metabolic Equivalents). The most well-known technique for measuring METs utilizes VO_2 (oxygen uptake) readings for a subject. However, VO_2 level measurements are typically done in a laboratory setting, which requires expensive and heavy mask to measure the amount of oxygen exhaled.

There has been much works that correlates heartrate to MET. In [6], variations in MET are mapped to adaptively control a pacemaker. The work in [7] describes how minute-by-minute heart rate measurements can be used for energy expenditure calculations. Upon comparison with calorimeter-based calculations, the paper shows that this is a suitable technique with a small error margin. Though the doubly labeled water technique [8] is still the most accurate method to measure energy expenditure, using heart rate and physical activity are simple, easy to measure and quite accurate techniques to achieve the same results.

Inertial information about the user's movement is also widely used in order to find correlation to the energy expenditure. The work in [9] describes an experiment in which total energy expenditure was calculated using a uniaxial accelerometer. In this study, simple and noninvasive techniques were used to produce an energy expenditure measure that linearly mapped to the MET calculated using standardized methods, which lends credence to the fact that our pedometer readings, along with heart rate measurements, can be utilized to build regression equations to calculate MET (or a MET-like measure) with a reasonable degree of accuracy. Similarly, [10], uses accelerometer counts to define equations that map to the energy expenditure of a subject.

There are several products on the market or described in prior research which collect and analyze health data using sensors mounted on the body. This information is either post-processed by downloading to a computing device after data is collected over a period of time or (more rarely) immediately transmitted to a base station for real time analysis [11]. For example, most of the devices listed in [6] are presently available in the market to be bought by consumers.

However, the aforementioned works often suffer from inaccurate calculation of energy expenditure using based on a single variable (e.g. either heart rate or accelerometer), or they are often limited to a controlled environment.

III. System Overview

The system described in this paper is a wireless health-monitoring device intended for monitoring an individual or entire group of subjects using a scalable architecture. Each sensor system is mounted onto the arm using a Velcro armband, as shown in Fig. 1. The sensory devices utilized in this work include a pulse sensor, a pedometer, and a temperature sensor. Readings are taken regularly and transmitted to an aggregator (e.g. a mobile device), which has a connection to a cloud database.

The received physiological signals are then processed in the aggregator to compute the energy expenditure estimate. The physiological data and computed energy expenditure are then delivered to a secured cloud server, to allow further analysis of the personal health record such as pulse history, movement history, tracking of energy expenditure, and accumulated energy expenditure. Moreover, the system can be configured for monitoring multiple users in real-time by activating the Multi-user Monitoring System. This system receives the processed data from multiple aggregators within its radio range. The graphical summary of the system architecture is provided in Fig. 2.

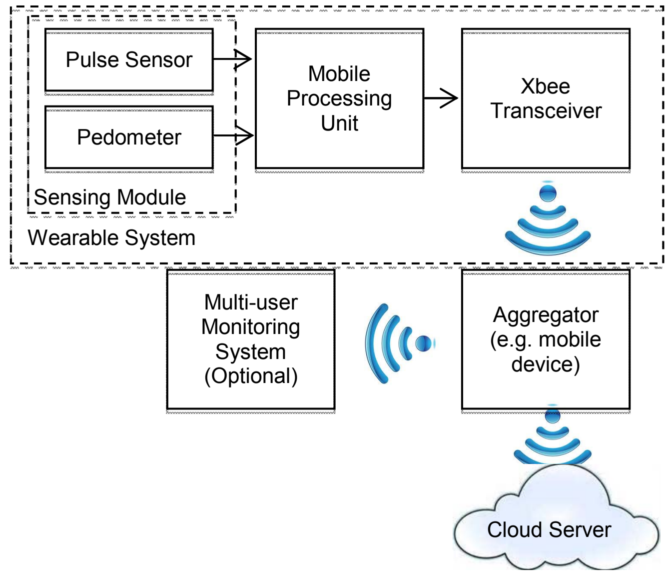

Fig. 2. Graphical illustration of the summary of the proposed system.

A. Sensing Modules

The sensors used in this system consist of a pulse sensor, a pedometer, and a temperature sensor.

1) Pulse Sensor:

The optical pulse sensor used in this system is lightweight, portable, affordable, and can be attached to a variety of locations such as the fingertip, or earlobe. This sensor works by detecting the amount of light that shines through skin. As blood is pumped through our capillaries, the volume of our capillary tissues varies, affecting the amount of light that shines through. These minor fluctuations can be detected using a photodiode and various other hardware components.

2) Pedometer

To determine speed and distance travelled, we chose to modify an inexpensive accelerometer-based pedometer. The raw signal from the pedometer is processed using a low-pass filter to remove noise, which is described in more detail in the next section. The output produced by the pedometer (i.e. the number of steps) is then converted to distance, and later, speed, based on the subject's stride length.

3) Temperature Sensor

The temperature sensor is not used to compute the energy expenditure but to provide more comprehensive physical information about the user to allow (i) further analysis on the user's physical performance and (ii) prevention of any hazardous health events such as heatstroke or heat exhaustion.

The temperature sensor used in this system is a thermocouple-based robust temperature sensor with a resolution of 0.1 degrees Celsius and a range of -40 to 125 degrees Celsius.

B. Mobile Processing Module

The firmware on the mobile processing unit consists of drivers to interface with the various sensors as well as a software program to transmit the data to the wireless module using Serial Peripheral Interface (SPI). Because data from multiple sensors is transmitted for multiple individuals, a simple and efficient protocol was required in which user ID, sensor type, and its data are encoded in an 8-character string. Three bytes represent the hexadecimal ID of the subject associated with the sensor reading, while two bytes identify the type of reading. This protocol therefore supports 4096 subjects and 256 message types.

C. Communication Module

The system's wireless transceiver is the 1mW XBee module, mounted on the sewable Lilypad Xbee board. The 1mW version with a range of 300 ft. was selected to conserve power, though more powerful varieties are available.

D. Aggregator

The major objective of the aggregator is to calculate the energy expenditure estimate (which is discussed in detail in Section 3) and to deliver the processed information to the cloud server or to the multi-user monitoring system if necessary. To improve the accuracy of the energy expenditure computation, the signals received from the sensory devices are pre-processed. The following two subsections describe the pre-processing for the pulse and the pedometer signals.

1) Signal Preprocessing – Pulse (Heart rate) Sensor

The optical pulse sensor can detect individual heartbeats, which are processed by the software to estimate heart rate. This is accomplished by averaging the time intervals between successive heartbeats and scaling to estimate beats per minute.

2) Signal Preprocessing – Pedometer

To estimate a subject's movement speed, the system must first read and filter the signal from the pedometer, which detects each individual step. When the acquired voltage crosses a threshold, a step is registered. However, due to noise, multiple steps may be registered for each actual step, as the acquired voltage will rapidly fluctuate around the threshold. Therefore, after each step is recorded, subsequent readings are disabled for several milliseconds. After determining the number of taken steps in the recent interval, the system estimates the distance covered based on stride length.

E. Multi-user Monitoring System

The Multi-user Monitoring System provides graphical summary of the captured sensory data in a user-friendly manner, bringing attention to subjects in distress and issues alerts when necessary.

An overall risk assessment is generated for each subject, and displayed in the rightmost panel. This allows the administrator (e.g. the coach) to quickly switch to the individual at greatest risk. Once the individual is selected, a full history of the subject's pulse data, temperature data, and distance data is displayed, with color-coding to illustrate the areas of alarm based on predefined thresholds. The risk assessments shown for each subject include heatstroke, cardiac arrest, and exhaustion. Another feature of the application is an energy expenditure estimate for each subject. A screenshot of the prototype system is provided in Fig. 3.

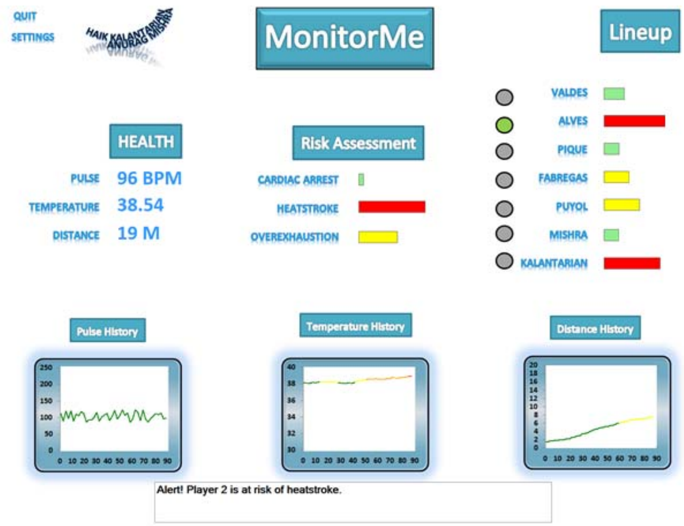

Fig. 3. A screen capture of the Multi-user Monitoring System

IV. Energy Expenditure Calculation

A standard method of estimating energy expenditure in fitness machines is to use the American College of Sports Medicine Metabolic Equations from [12], which estimates and scales oxygen consumption from movement speed and surface incline, and scale to total energy expenditure based on the weight of the subject and the duration of the exercise. These equations provide relatively accurate energy expenditure calculations, but are limited for use in a controlled environment (e.g., a treadmill at known speeds) and are not suitable for a mobile system. The major challenges arise from inaccuracies in the pedometer's assessment of movement speed, which significantly affect the accuracy of the caloric estimate. To minimize the error, it is possible to combine data from multiple sensors, therefore mitigating the impact of one inaccurate sensor.

As discussed earlier, heart rate and movement speed are the two most important pieces of information in estimating the energy expenditure [5]. Since the mobile environment is highly dynamic, we propose to construct an empirical energy expenditure equation of these two variables using a linear regression model:

$$E = A * S + B * P + C, \quad (1)$$

where E, S, and P represent energy expenditure, speed, and pulse, respectively. A, B, and C are the coefficients that minimizes the mean absolute error between the proposed energy expenditure estimate and the estimate computed by the standard method [12].

A linear regression was used to generate optimal coefficients *A*, *B,* and *C.* Thus, by calculating the optimal coefficients, the accuracy of the estimate from a mobile health-monitoring system was able to approach that of a stationary system with known speeds.

V. Experimental Procedure

In order to validate the accuracy and the efficacy of the proposed system and the energy expenditure estimate equation, an experiment with three participants was performed. The three subjects walked on a treadmill at various known speeds for fixed periods of time in order to test the system at different speeds.

The validated standard method to estimate the energy expenditure in controlled treadmill machine is as follows. When a subject is walking, the formula for VO_2 is

$$VO_2 = 0.1(s) + 1.8\,(s)(f) + 3.5, \tag{2}$$

where *s* is the speed in miles/hour and *f* represents the incline of the surface [12]. When running, the following formula is typically used:

$$VO_2 = 0.2(s) + 1.8\,(s)(f) + 3.5. \tag{3}$$

After VO_2 is estimated in ml/kg/min using the formulas above, this value is converted to kcal/min based on the subject's weight. This is subsequently multiplied by the duration of exercise to produce total energy expenditure in calories. Because a subject's movement speed may vary, energy expenditure rates can be calculated at regular intervals, producing a net expenditure sum which is updated regularly.

This calculated energy expenditure rate was used as a baseline for assessing the accuracy of other methods, since the speed of movement on a treadmill is precisely known.

Simultaneously during this experimentation, the mobile monitoring system periodically reported pedometer-based estimated movement speed and heart rate. Thus, the experiment produced (i) the energy expenditure estimate computed by (2) and (3) using known speeds based on the configuration of the treadmill, and (ii) the estimate computed by the proposed equation in (1) using raw sensor data from the wearable health monitoring system, fit using linear regression to estimates from (i).

Furthermore, in order to compare the accuracy of the proposed estimation method against conventional pervasive systems that only consider accelerometer data, a linear regression model was developed without the pulse sensor, simply relating the pedometer's reported speed to energy expenditure. This model is defined by the equation below:

$$E = A * S + C. \tag{4}$$

Lastly, a third linear regression model was developed to measure the accuracy of energy expenditure using the pulse sensor alone.

During this period, each subject's heart rate was recorded at regular intervals, as reported by the treadmill in order to evaluate the accuracy of the pulse sensor embedded in the proposed system.

Because data was collected from three subjects at 6 different speeds that ranged from walking to running, the linear regression tool was applied to the data collected from all three subjects in order to obtain the globally optimized estimate. The intent of using multiple subjects is to derive an energy expenditure model that can be used on an arbitrary subject without extensive calibration. This explains the inaccuracy of the model which simply correlates heart rate with energy expenditure. Because of dramatic differences in the resting heart rate of different subjects, as well as differences in their cardiovascular fitness levels, relying too heavily on pulse for an energy expenditure estimate will lead to erroneous data unless the device is calibrated to that particular individual's fitness level. Furthermore, even if the device is calibrated to an individual subject, the high standard deviation of the optical pulse sensor would lead to inconsistent energy expenditure rates. This sensor is therefore better served as a secondary source of information rather than a primary heuristic for energy expenditure calculation, which is confirmed by our experimental results.

The movement speeds included in the experimentation ranged from 1 mph to 6 mph, in intervals of 1 mph. This range adequately covers both walking speeds and running speeds. For the theoretical model of energy expenditure used as a baseline, equation (2) was used for speeds of 1, 2, and 3 mph while equation (3) was used for speeds of 4 mph and above. Three subjects were selected to walk at all 6 speeds for 5 minutes, each. The coefficients for the linear regression model were specifically chosen to minimize the global error of the estimate for all three subjects across all 6 speeds.

VI. Experimental Results

A. Results

The expenditure estimate based on movement speed was poor due to the inaccuracy of the pedometer. When compared to the VO_2-based model, the mean absolute error of this method was 16.18, based on Calories burned. The sensor fusion model reduced Mean Absolute Error (MAE) to 5.77 compared to the golden model, which is a reduction of 64.3% compared to the pedometer fit, as shown in Fig. 4. This is also a reduction in error of 56.2% compared to the pulse-sensor fit, which attempts to estimate energy expenditure from heart-rate alone. Error is defined as the discrepancy between the regression model's estimated energy expenditure, and that of the VO2 model based on the treadmill's configuration and heart rate sensor. Fig. 5 shows estimate accuracy at various speeds, with data averaged from all three subjects.

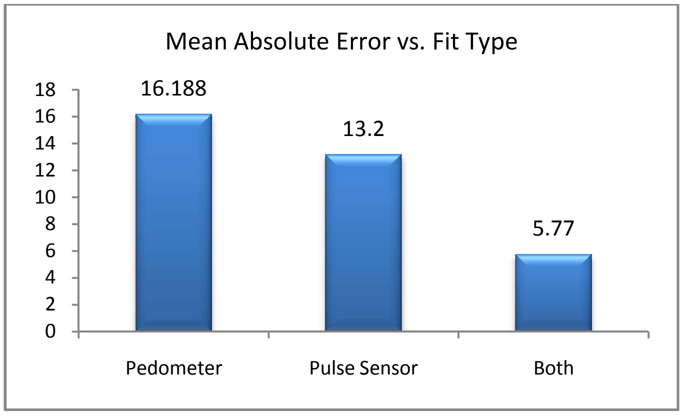

Fig. 4. The mean absolute error of energy expenditure estimation (Calories) using various heuristics include speed, HR, and both

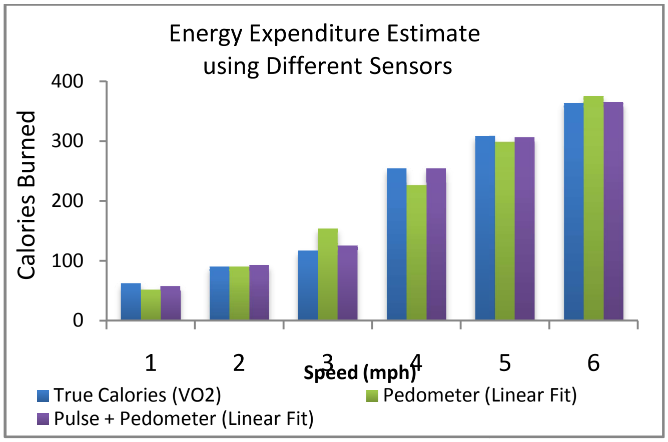

Fig. 5. Accuracy of energy expenditure estimate using speed, heart rate, and a combination of these two sets, for 30 min two sets for 30 minutes of activity

For the combined model, the optimal coefficients A, B, and C for equation (3) were determined to be 11.16, 2.47, and -174.41 for units of Calories burned per hour. The regression fit using these coefficients is based on data collected from three subjects, to account for variations in walking style, height, and cardiovascular fitness levels. Furthermore, data was collected across 5 minutes of activity at 6 different speeds from 1-6 MPH. Therefore, this model can be reliably used for different subjects without requiring extensive calibration to each individual's walking style, or resting heart rate. An energy expenditure approach relying too heavily on one particular sensor is of limited value due to significant variations from one individual to another. By using multiple sensors, the impact of individual variations is reduced significantly, as confirmed by our experimental results.

Fig. 6 shows the accuracy of the estimate for one subject during 5 minutes of walking at a fixed speed. This figure illustrates the improvement in estimate accuracy for the majority of the duration of the exercise, as a result of combining data from multiple sensors. The sensor-fusion based model differs from the VO_2 mathematical model for energy expenditure at a known speed by an average of 3.05%, compared to 10.92% for the pedometer.

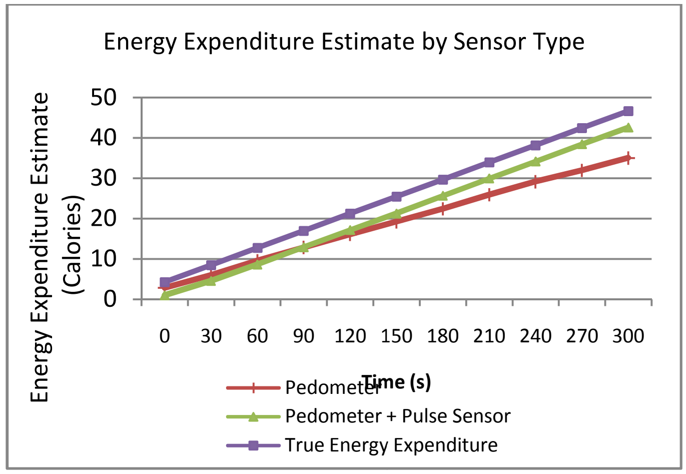

Fig. 6. Accuracy of the energy expenditure estimate using only data from the pedometer vs. the combined model, for one subject at 4 MPH

In this experiment, surface inclination is assumed to be 0, because the system was originally designed to track player health during a sports activity such as soccer or basketball, which would typically take place on a level field. However, with the addition of additional sensors such as a gyroscope, this parameter could be included in the calculation as a future work.

B. Pedometer Accuracy

Several factors contribute to the inaccuracy of the pedometer. First, a significant number of false-positives occur when recording the number of steps reported by the pedometer into the system, because of noise in the electronic interface between the pedometer and aggregator. Therefore, the pedometer's accuracy varied significantly with movement speed.

Another contribution to the error occurs during the conversion process between the number of steps taken during an interval and distance travelled. This conversion process varies between individuals depending on height, gender, physique, speed, and walking style. Due to the high standard deviation in the pedometer's reported speed, the high standard deviation for even one subject at a fixed movement speed would limit the usefulness of this approach. Furthermore, extensive individual calibration may not be practical in a commercial system.

C. Pulse Sensor Accuracy

Fig. 7 shows the mean-squared error between the data reported by the pulse sensor and that reported by the treadmill. Because of the relatively large error of the pulse sensor readings, as well as the high standard deviation from one reading to another, we find it impractical to estimate energy expenditure using a pulse sensor alone while maintaining the budget and mobility constraints of a wearable health-monitoring system such as the one described in this paper.

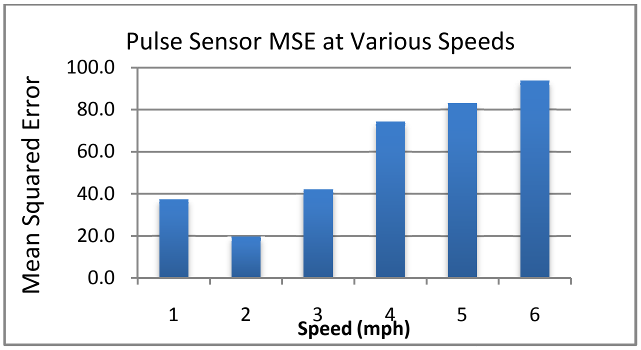

Fig. 7. Mean-squared error of the pulse sensor readings (BPM)

TABLE I
COMPARISON OF TREADMILL SPEED TO PEDOMETER'S REPORTED SPEED IN MPH

Actual speed	1	2	3	4	5	6
Reported Speed	.8	1.7	3.2	4.9	6.6	8.4
St. Deviation (Reported)	.49	.44	.40	.51	.64	.91

VII. CONCLUSION

This paper describes a wireless health monitoring system that measures the heart rate, speed, and body temperature, and computes accurate energy expenditure estimation in remote environment. This system is subsequently used as a platform for mobile energy expenditure estimation research. We propose a novel method to estimate energy expenditure using data collected from both a pedometer and pulse sensor, which we show is significantly more accurate than an estimate using data from one sensor alone, and does not require extensive calibration for each subject This method reduces the mean-absolute error of the estimate by 64.3% compared to the pedometer model and 56.2% compared to the heart-rate model. These results prove that in a multi-sensor system consisting of a pedometer and pulse sensor, an accurate energy expenditure estimate can be calculated despite inaccuracies in individual sensors.

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