Proceedings of the Twenty-Second Innovative Applications of Artificial Intelligence Conference (IAAI-10)

Ambulatory Energy Expenditure Estimation: A Machine Learning Approach

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Abstract

This paper presents a machine learning approach for accurate estimation of energy expenditure using a fusion of accelerometer and heart rate sensing. To address short comings in existing off-the-shelf solutions, we designed Jog Falls, an end to end system for weight management in collaboration with physicians in India. This system is meant to enable people to accurately monitor their energy expenditure and intake and make educated tradeoffs to reach their weight goals.

In this paper we describe the sensing components of Jog Falls and focus on the energy expenditure estimation algorithm. We present results from controlled experiments in the lab, as well results from a 15 participant user study over a period of 63 days. We show how our algorithm mitigates many of the issues in existing solutions and yields more accurate results.[1]

Introduction

The statistics of rapid increase in obesity, and its effect on diabetes, heart disease and high blood pressure has motivated much of this work. To enable people to better manage their weight, we need to empower them with solutions to monitor their energy expenditure and balance it against their food intake. Accurate visibility of these parameters provides people with the necessary information to make educated tradeoffs. In addition, enabling users to share this knowledge with their physicians enhances the physicians' ability to help their patients. There are many off the shelf solutions available today to measure energy expenditure such as pedometers, Body Bugg, Nike+, and many others. However, most of these solutions have limitations when it comes to accuracy, system integration, and user feedback. To realize this vision, we worked closely with physicians to design an end to end system for weight management that addresses the shortcomings in existing solutions. Our system, which we call Jog Falls, consists of multiple sensing devices (accelerometers and heart rate sensor) connecting to a cell phone for further processing, aggregation and data transport. To satisfy the accuracy requirement for energy expenditure estimation, we designed an algorithm that fuses data from the different sensors. This fusion approach improves the accuracy and helps mitigate issues like sensor noise and data loss. We conducted a user study on 15 participants over a period of 63 days and analyzed the results of the study.

In this paper we describe this algorithm and show results from controlled experiments as well as our user study.

The rest of the paper is organized as follows. We first describe related work, followed by a system overview. We then describe the details of the algorithm and the features used, followed by a description of the results from the controlled experiments and the user study. We finally conclude the paper and describe future work.

Related Work

Several solutions to calculate ambulatory energy expenditure have been proposed. Most notable work that takes a machine learning approach is BodyBugg. As described in [McClain, James J 2005] and [David Andre. 2006] BodyBugg shows better accuracy in estimating Energy Expenditure by using sensors like GSR (galvanic skin response) and heat flux to compensate for the shortcoming of accelerometers in accurate effort estimation. However, as shown in the experimental results section, it overestimates expended energy due to error in estimating body movement (e.g. while riding in vehicles). The authors in [McClain, James J 2005] also demonstrate accuracy improvement by using heart rate data with BodyBugg sensors, but since the principle of operation of the device is based on identifying user context and choosing the right formula accordingly to calculate EE, it will still be affected by the lack of lower body information.

[Soren Brage 2004] used a hip mounted single axis accelerometer to quantify the level of physical movement in terms of "counts per minute" for walking and running speeds. They used a Branched Equation Model, however, the model does not consider energy expenditure due to "upper body" movement during sedentary activities (like working on PC, bending, arranging drawers, cooking, ironing etc) hence leading to underestimation of energy expenditure. Another shortcoming of their solution is that if one of the sensors stops providing data, the system will not output any energy expenditure. We address both of these limitations in our solution. [K Rennie 2000] used a single integrated chest mounted movement and HR sensor. They address the effect of emotion on HR and the quantification of excretion, however, the algorithm will be affected by the lack of lower body movement data.

Results from [Daniel Olgun 2006] and [Ling Bao 2004] prove that a combination of accelerometer data from upper and lower body always yields higher accuracy in identifying user activities, compared to a single accelerometer. The errors are mainly due to the misinterpretations of the movement noise caused in the accelerometer. The same conclusion could be extended to the technologies described in [Soren Brage 2004][K Rennie 2000][McClain, James J 2005] and [David Andre.2006], which use a single accelerometer either on the upper or lower body for EE calculation.

System Overview

Our Energy Expenditure estimation system contains the following components:

Chest Sensor

The Chest Sensor (CS), designed in-house, is comprised of a wearable ECG Heart Rate (HR) monitor with an integrated 3-axis accelerometer sensor. The CS uses the integrated Chest Accelerometer (CA) to estimate the intensity of upper body movement (such as bending, turning, movement of hands) in terms of Metabolic Equivalents (METs), which we refer to as CA_MET. The CS sends computed HR and the CA_MET values to a cell phone, wirelessly over Bluetooth, every 5 seconds.

Hip Sensor

The Multi-sensor Platform [MSP], which also has an integrated 3-axis accelerometer, is used as Hip Sensor (HS). The signals from the Hip Accelerometer (HA) are classified using machine learning algorithms to identify user activity (sitting, walking, running etc) and walking speed. The HS sends the walking speed (S) and activity information to the cell phone, wirelessly over Bluetooth, every 5 seconds.

Data Aggregator

The Cell phone runs the Data Fusion algorithm which fuses data from HR, CS and HS to estimate the EE every minute. The cell phone continuously aggregates computed values from the CS and the HS, averages the values over a minute and passes it to the Data Fusion algorithm. All the computed values are stored on a flash card and used for post-analysis.

Individual Calibration

Energy requirement of any activity can also be quantified in terms of METs. Each activity has a specific MET value, proportional to the required effort. Multiplying MET by the Weight (W) of the individual in Kg gives the EE in kcal per hour. MET values published in the Compendium of Physical Activities [Ainsworth 2000] were used.

Heart Rate Calibration

Since both EE and HR are proportional to Oxygen Uptake (VO_2), HR can be used to estimate EE. However, as HR at particular activity intensity depends on the fitness level of the individual, HR needs to be calibrated for each individual to estimate EE. In our calibration procedure, subjects walked for 3 minutes each, at different walking speeds, during which their HR and MET equivalent to the walking speed were noted to build an individualized HR v/s MET calibration table. Before the start of the calibration procedure, subject's Resting Heart Rate (RHR) was also noted.

Accelerometer Calibration

The CA was used to quantify the activity intensity of low-intensity, non-walking activities which involve the upper body movements. Signals from 3-axis of the CA, were combined and averaged to form a composite signal, proportional to the upper body movement. BodyBugg has been shown to be accurate at estimating the resting energy expenditure [Malavolti 2007] [Fruin 2003], it was also verified in our Controlled Calorimeter experiment. Hence, the average magnitude of this composite signal was calibrated in the range of 0 to 3 METs while performing different sedentary activities (like sitting and working with hands, bending, cleaning, ironing, arranging drawers), using BodyBugg as reference. We refer to the METs estimated by the CA as CA_MET. Performing any activities with intensity greater than or equal to slow walk will result in a CA_MET value exceeding 3.

Theory of Operation of Fusion Algorithm

The features extracted from hip, chest accelerometer and heart rate are used to determine the best possible sensor to calculate Energy Expenditure (EE) for a given context. This enables a comprehensive analysis of user's physical state and amount of exertion in an activity. In addition it allows mitigating failures caused by missing data or sensor failure. Some of the cases addressed by our algorithm that differentiate our solution are listed below.

- Psychological & emotional factors influence heart rate leading to higher estimation of EE. The Fusion algorithm uses heart rate trending in conjunction with lack of movement in the upper and lower body to identify the emotion effect on heat rate and calculate EE based on the accelerometer.
- During the recovery phase of an exercise, heart rate tends to overestimate the expended energy, while the accelerometer tends to underestimate it. The fusion algorithm adopts a switching technique that minimizes the error by using heart rate during the initial ramp down and switching to accelerometer after the ramp down of the heart rate.
- Vibrations in a moving vehicle could influence the accelerometer leading to higher estimation of EE. The fusion algorithm is designed to identify the condition and switch to the heart rate sensor.
- Accelerometer can't estimate effort accurately (e.g. tell the difference between walking or walking while carrying a heavy load). The fusion algorithm can identify this context and use heart rate which will be more representative of the effort.

Choosing a single best sensor from all available sensors allows the fusion algorithm to gracefully degrade during sensor failures, and continue operation by using the information from the existing sensors. Alternative approach is to estimate a combined MET value from the sensors. We took the former approach due to our familiarity with context recognition and the fact that many of the components were already developed.

BayesNet Model

We used Bayesian Network to infer the validity of the sensors. The network structure learnt using data from our controlled experiment is shown in Figure 1. The decision variables like "HR Validity", "Upper Body Accel Validity" and "Lower Body Accel Validity" are binary variables, representing valid and invalid states with equal priors. The feature variables consist of states representing discrete value ranges learnt from the training data. Three different queries $P(HR\,|Evidence)$, $P(LowerBody\,|Evidence)$, and $P(UpperBody\,|Evidence)$ will be performed on the network after extracting features from the sensor data to calculate conditional probability of validity of each sensor. The query that returns the highest probability is chosen as the preferred sensor.

For example, in the case of a weight lifting, the upper body accelerometer will tend to record higher movement than the lower body and at the same time heart rate of the subject will be elevated well above normal. The above evidence affect the individual probability of the nodes as follows,

$$P(Upper\ Body\ MET > 3\ |Upper\ Body\ Accel\ Valid = T) \rightarrow 0$$

$$P(Lower\ Body\ Speed = 0\ |DeltaHR = High, HRValid = F, Lower\ Body\ Accel\ Valid = F, Upper\ Body\ Accel\ Valid = T) \rightarrow 0$$

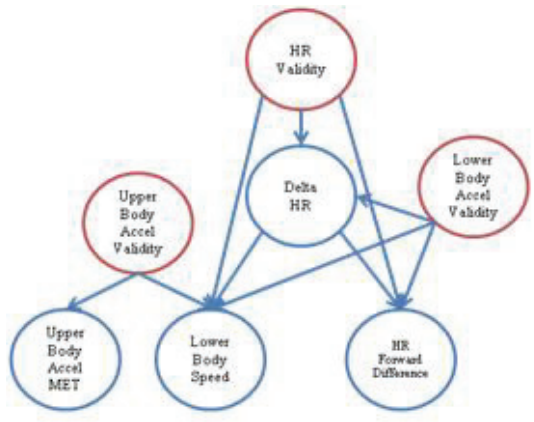

Figure 1 BayesNet for sensor validity

$$P(Lower\ Body\ Speed = 0\ |DeltaHR = High, HRValid = F, Lower\ Body\ Accel\ Valid = T, Upper\ Body\ Accel\ Valid = F) \rightarrow 0$$

$$P(Lower\ Body\ Speed = 0\ |DeltaHR = High, HRValid = T, Lower\ Body\ Accel\ Valid = F, Upper\ Body\ Accel\ Valid = F) \rightarrow 1$$

And

$$P(DeltaHR = High\ |\ HRValid = T, Lower\ Body\ Accel\ Valid = F) \rightarrow 1$$

The local probabilities favor $P(HRValid\,|Evidence)$ compared to the other queries and thus influencing the decision to choose Hear Rate sensor.

Similarly, in case of vehicle noise, the local probabilities look as follows

$$P(Upper\ Body\ MET > 3\ |Upper\ Body\ Accel\ Valid = T) \rightarrow 0$$

$$P(Lower\ Body\ Speed > 1\ |DeltaHR = Low, HRValid = F, Lower\ Body\ Accel\ Valid = T, Upper\ Body\ Accel\ Valid = F) \rightarrow 0$$

$$P(Lower\ Body\ Speed > 1\ |DeltaHR = Low, HRValid = T, Lower\ Body\ Accel\ Valid = F, Upper\ Body\ Accel\ valid = F) \rightarrow 1$$

Thus reducing the chances of picking the noisy accelerometers for calculating EE. It is worth observing the indirect influences in the graph. For example, the "Upper Body Accel MET" influences "HR Validity" and "Lower Body Accel Validity" when "Upper Body Accel Validity" is not observed. Similarly the HR Features affect the "Upper Body Accel Validity" through the "Lower Body Speed".

It is evident from examples above that features from all the sensors will either directly or indirectly influence all three of the decision nodes, and thus reinforcing each other in choosing the right sensor for a given context.

Sensor Features

Delta Heart Rate: This feature represents the difference between the mean heart rate of a given 1 minute window and the resting heart rate of the subject. The delta value is split in to 3 discrete ranges which form the elements of the random variable set.
Heart Rate Forward Difference: This feature represents the mean value of forward difference of heart rate in a given 1 minute window. The feature provides the trending of the HR data in a given window. For example, was the HR consistently reducing, increasing or stayed almost flat.
Lower Body Speed: This feature represents the speed of movement of the lower body using hip accelerometer. It can capture walking and running speed in MPH.
Upper Body MET: This feature provides a metabolic equivalent of the movement captured in the upper body accelerometer.
Mean Heart Rate: This feature provides the mean heart rate for any given minute.
Heart Rate Mean difference: This feature represents the difference in mean heart rate across successive window. It provides information about the trend of heart rate across windows.

Model Learning

A supervised learning approach was adopted to create the model. The training examples are generated by using data from the lab experiment described in the "Calorimeter Experiment" section below. We used WEKA [Witten 1999] for learning the structures and parameters of the BayesNet. The structure of the BayesNet and the CPT (Conditional Probability Table) for the random variables are learnt using K2 greedy search algorithm with Bayes estimator. We compared the inference results by learning network with three and four maximum parents per node and found that adding an additional parent to the variable did improve the inference and hence decided to go with four parents.

Inference and EE Calculation

The BayesNet consists of 3 decision nodes, each attempt to answer the validity question of one of the sensors. For example, if the question we want to answer is P(HR Validity) we will observe the nodes, "Delta HR", "Lower Body Speed", "Upper Body MET" and "HR Forward Difference".

The probability of decision variable is calculated using Baye's rule, given all the features from various sensors. Let HR represent the class variable for "Heart Rate Validity". Let E represent all the other random variables used as evidence.

Let HR = {v, nv}, be the states representing HR Valid and HR not valid. $P(HR = v|E) = \frac{P(E|HR=v)P(HR=v)}{\sum_{HR} P(HR,E)}$ (1)

The joint probability of the BayesNet using chain rule can be written as

$$P(HR = v, E) = P(E|HR = v)P(HR = v) \quad (2)$$

Similarly,

$$P(HR = nv, E) = P(E|HR = nv)P(HR = nv) \quad (3)$$

Applying 2 and 3 in 1

$$P(HR = v|E) = \frac{P(E|HR=v)P(HR=v)}{P(HR=v,E)+P(HR=nv,E)} \quad (4)$$

Thus the CPD associated with each variable given its parents can be used to calculate the joint probability and ultimately the conditional probability of the class variable.

Similar queries can be formed for "Lower Body Accelerometer Validity", and "Upper Body Accelerometer Validity".

In case of missing data from one of the sensors, the algorithm allows to integrate over missing variables in the graph, facilitating a smooth operation. For example, let E_{MSP} be the evidence from lower body accelerometer and E represent the evidence set from rest of the sensors. In the case of missing lower body accelerometer data, equation (4) can be written as follows,

$$P(HR = v \mid E_{MSP}, E) = \frac{\sum_{E_{MSP}} P(e_{MSP}, E \mid HR = v)P(HR = v)}{\sum_{E_{MSP}} (P(HR = v, e_{MSP}, E) + P(HR = nv, e_{MSP}, E))} \quad (5)$$

We designed the energy expenditure calculation to be performed every minute to help average erroneous input from the sensors that could lead to wrong sensor choice.

Experiment and Results

This Section describes the experiments performed for training and validating the system, together with the results from the deployment.

Calorimeter Experiment

A lab experiment was conducted in the Human Performance Laboratory of Oregon Health Science University. The experiment aimed at understanding the limitations of the sensor data like Heart rate, lower and upper body acceleration in comparison to Calorimeter which is considered as one of the golden standards for calculating EE. The calorimeter (Figure 4) is a device that measures the oxygen uptake and requires inserting a large fixture into the mouth and plugging the nose to ensure that oxygen flow is fully captured and measured through the device. It is uncomfortable to wear and restricts the person's movement quite a bit, so we needed to give frequent breaks to subjects while performing the experiment. As a result, it is not an option to use the calorimeter in real settings, but it is a great tool for performing controlled experiments and calibrating other equipment.

Four subjects wearing a hip mount accelerometer, BodyBugg (arm mounted with multiple

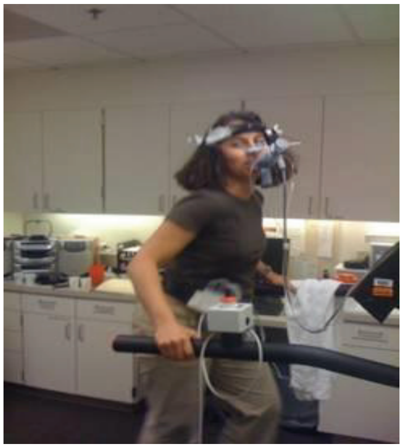

Figure 4 One of the authors in Calorimeter setup

sensors)[BodyBugg], Polar HR monitor [Polar] were connected to the Calorimeter. Required parameters like, lower / upper body movement, heart rate, and EE from the calorimeter were logged. Subjects were asked to perform five different activities like slow walking, brisk walking, running, weight lifting and biking while connected to the calorimeter. Each activity was followed by a break where the user had to sit quietly. The initial 20 minutes were used to collect resting heart rate while sitting quietly and working on computer. However we observed elevated heart rate on all subjects (possibly anxiety induced) and repeated the RHR measurement in a different setting when the users were not connected to the calorimeter.

The data from the experiment was used to train the fusion algorithm in such a way that the modality chosen for EE calculation will maximize proximity to the Calorimeter. Cases like exercise recovery, upper body workout and the effect of exertion were captured accurately in the training. Cases like moving vehicles, and emotional effect were added to the BayesNet after the training process, since it was hard to collect data for such situations in a lab setting. The CPT's were adjusted using sensitivity analysis tools to address these conditions.

Figure 5 shows that heart rate sensor was chosen for high activity level whereas accelerometer sensor was chosen when the user was sedentary. In addition heart rate sensor was chosen for a brief period of time while recovering from an intense activity. The decision to switch to the accelerometer in this situation is driven by the rate of change of heart rate, as it decreases the algorithm switches to the accelerometer to prevent MET over-estimation.

It can be seen from Figure 3 that heart rate overestimates the MET values in multiple occasions. There is an overestimation immediately after an intense activity, where the heart rate does not recover quickly, leading to a higher MET value. Secondly, at the beginning of the experiment the anxiety effect of wearing the calorimeter equipment resulted in an elevated heart rate in all of the four subjects which also caused a higher MET value estimation. The accelerometer shows a close proximity to the calorimeter

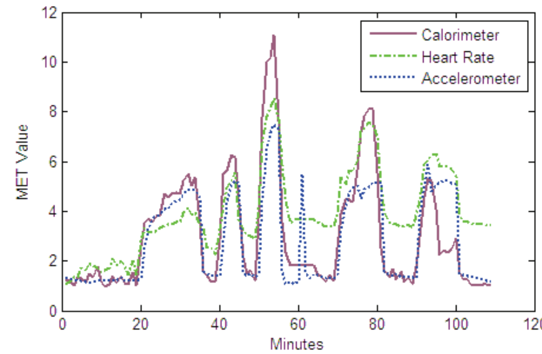

Figure 3 Compare MET values of Heart rate and accelerometer with calorimeter

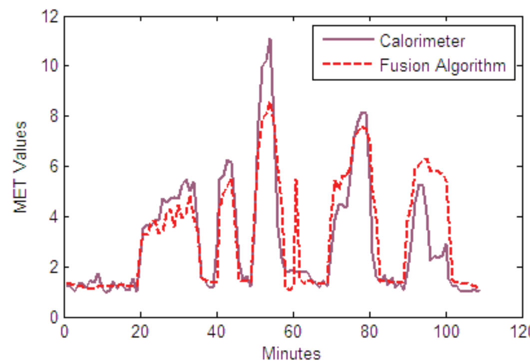

Figure 2 Compare MET value of Calorimeter and Fusion Algorithm

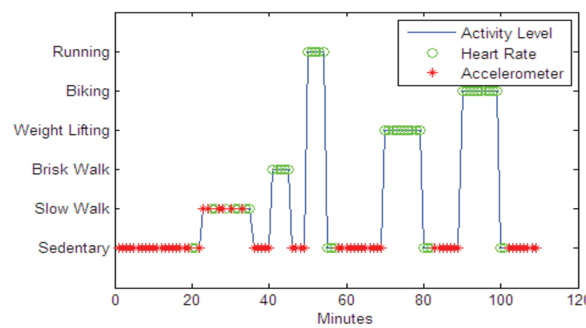

Figure 5 Sensor choice for different activity context

during sedentary states, but underestimates exertion in the intense activities, as shown in the figure for cases like weight lifting and running.

The fusion algorithm was designed to choose the right sensor based on user activity level to obtain a MET value close to the calorimeter estimation. Results showed that the heart rate sensor overestimated EE by (+22%) and the accelerometer underestimated the effort by (-10%). The fusion algorithm reduced the error to (+5%) by switching between the heart rate and accelerometer sensor at the right context. Figure 2 illustrates the proximity of MET values between the fusion algorithm to the calorimeter.

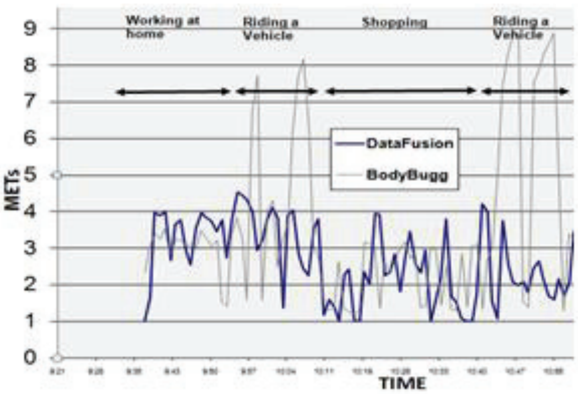

Figure 7 Performance of Data Fusion algorithm and Bodybugg while traveling in a vehicle

Comparative Experiments

Bodybugg has been shown to be accurate at measuring total Energy Expenditure in free living conditions [St-Onge 2007]. In order to compare the performance of our data fusion technique with BodyBugg, subjects also wore Bodybugg along with our test setup. Minute by minute EE measurements were logged while subjects performed different activities in free living conditions (desk work, cleaning, washing, cooking, walking, shopping, sleeping, traveling in vehicle). Our algorithm closely tracked EE estimated by Bodybugg for most activities, the aggregate results of which are shown in Table 1. However, BodyBugg overestimated EE, equivalent to running (9 METs), even when the user was sitting in the vehicle while traveling. It does not seem to handle the vibration noise from the vehicle that affects the accelerometer, even with additional input from sensors like heat flux, temperature, and skin conductivity.

Table 1. EE estimated by fusion algorithm and by Bodybugg.

Test	Data Fusion (kcal)	Bodybugg (kcal)	% difference
Home Activities	319	340	-6%
Working at Desk	128	125	2%
Full Day Test	1308	1378	-5%

Our algorithm uses CA_MET as one of the inputs to switch between sensing modalities. For low intensity activities (CA_MET <= 3) the CA is used for EE estimation, whereas for moderate to higher intensity activities (CA_MET > 3), HR is used for EE estimation. While traveling in the vehicle, the composite signal from the CA exceeded 3 METs due to vehicle vibrations and jerks, causing the algorithm to switch to HR modality, and prevented the overestimation of EE. The results during vehicle travel are shown in Figure 7.

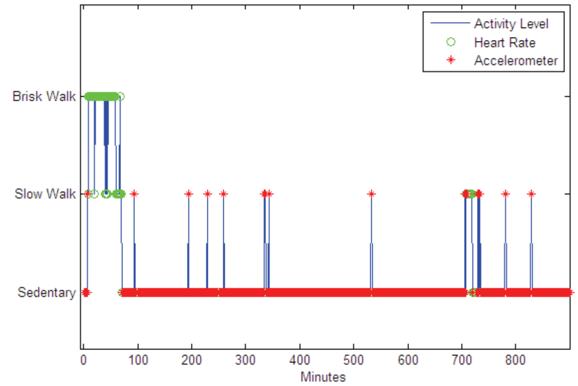

Figure 6 Sensor choice in JogFalls for various activities

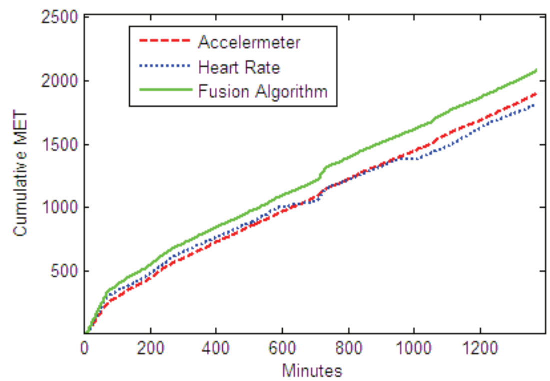

Figure 8 Comparing cumulative MET for accelerometer, Heart Rate and Fusion algorithm

JogFalls Study

The section describes results from the user study that we conducted at a leading medical school in India. The study involved 15 participants, who used the system for a period of 63 days. Estimation of EE in an accurate and reliable manner was a firm requirement of the study. Figure 6 shows the sensor choice made by the fusion algorithm during different activities. Comparing the sensor choices in Figure 5 and Figure 6 it is clear that the sensor choice for calculating energy expenditure during the deployment matches the results from the calorimeter test. Figure 6 also highlights the short bursts of "slow walking" spread across the day which did not have the intensity to influence heart rate as the preferred sensor.

Figure 8 shows the cumulative MET value for one day. Both accelerometer and heart rate , estimated 15-20% less than the fusion algorithm. The main cause of underestimation in the case of heart rate is the intermittent data loss possibly due to bad wireless connection. The fusion algorithm used accelerometer to calculate EE when there was no information from Heart Rate sensor. The accelerometer underestimated the expended energy for activities like Brisk Walking, however the fusion algorithm chose to use Heart Rate sensor, which is more accurate during those scenarios.

Data from our field study revealed the average run time of the application was 13 hours a day and about 30% of the time the system operated with only one of the sensors (due to battery and/or wireless communication issues), which led to data loss. In these cases, the BayesNet algorithm enabled integration over missing variables to calculate EE when one of the sensors is missing, thus resulting in graceful degradation of the system.

Conclusion

The paper described a machine learning approach to accurately calculate Energy Expenditure in ambulatory conditions, using data from a chest mounted and hip mounted Accelerometer together with heart rate. A context driven sensor choice using BayesNet algorithm proved to be much more effective than the existing techniques and estimated EE much closer to the golden standard. The algorithm utilizes the asymmetry in the failure conditions across the sensors to compensate for the limitations of each individual sensor.

We discussed various techniques used to calculate Energy Expenditure in this paper. While some are restricted to laboratory settings, few of the techniques used in products like BodyBugg utilize a combination of sensors like accelerometer, body temperature and galvanic skin response either individually or in combination and have been used in ambulatory conditions. Our experiments proved that the existing products do not address many of the failure cases like vehicle noise in accelerometer, psychological & emotional effects on Heart Rate etc. In addition, the controlled experiment proved that accelerometer underestimates exertion and hear rate overestimates recovery from an intense activity. The result section demonstrated that the fusion algorithm addresses the failure cases described above by switching to appropriate sensor in the right context.

Features from all three of the sensors were used in evaluating the current valid sensor in the BayesNet (Figure 1). However the mapping of lower body speed to MET values was based on [Ainsworth 2000] and was not individually calibrated for each user. In addition our training set was not extensive enough to claim generality of the solution. Hence we did not use the lower body accelerometer to calculate MET value even if it was chosen as the preferred sensor. We override that particular decision and choose HR or Upper body accelerometer depending on their validity. We intend to address this issue in our future revisions to further improve our solution.

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