Counting calories without wearables: Device-free Human Energy Expenditure Estimation

Habibur Rahaman
School of Computer Science and Technology
University of Bedfordshire
Luton, LU1 3JU, UK
md.rahaman@study.beds.ac.uk

Vladimir Dyo
School of Computer Science and Technology
University of Bedfordshire
Luton, LU1 3JU, UK
vladimir.dyo@beds.ac.uk

***Abstract*—Maintaining certain physical activity levels is important to prevent or delay the onset of many medical conditions such as diabetes, or mental health disorders. Traditional calorie estimation methods require wearing devices, such as pedometers, smart watches or smart bracelets, which continuously monitor user activity and estimate the energy expenditure. However, wearable devices may not be suitable for some patients due to the need for periodic maintenance, frequent recharging and having to wear it all the time. In this paper we investigate a feasibility of a device-free human energy expenditure estimation based on RF-sensing, which recognises coarse-grained user activity, such as walking, standing, sitting or resting by monitoring the impact of a person's activity on ambient wireless links. The calorie estimation is then based on Metabolic Equivalent concept that expresses the energy cost of an activity as a multiple of a person's basal metabolic rate using Harrison-Benedict model. The experimental evaluation using low cost IEEE 802.15.4 transceivers demonstrated that the approach estimated energy expenditure within an indoor environment within 7.4% to 41.2% range when compared to a FitBit Blaze bracelet.**

***Index Terms*—activity recognition, IoT, energy expenditure estimation**

I. Introduction

Sedentary lifestyle is known as a 'silent killer' [19] due to its detrimental effect on health and potential risks of developing chronic diseases such as type 2 diabetes, stroke and heart disease [21] [20]. While wearable technology such as activity trackers or smartwatches became popular to monitor physical activity levels and encourage physical lifestyles [10], they require periodic maintenance [36], such as recharging or replacing batteries which some users including elderly people cannot be relied upon to perform regularly or reliably. In addition, some people prefer not to wear electronic devices for personal reasons or other health conditions [8] [35].

Recently, RF-sensing technique has been proposed to detect human motion by analysing its impact on the parameters of surrounding wireless links. RF-sensing exploits the phenomenon that the human body, which consists of approximately 60% water, reflects, scatters and attenuates radio waves [37] and causes signal strength disturbances in a ambient wireless links which can be measured by conventional wireless transceivers. Since the pattern of these disturbances depends on the human position in relation to a mesh of wireless links, the person's location, motion or activity can be detected using machine learning and statistical analysis techniques. The advantage of RF-sensing is that it can operate without attaching any wearable device or instrumenting the indoor space with specialised equipment. Unlike image or video based activity tracking methods, the technique is non-intrusive has minimal privacy implications, and does not require cooperation from the user. RF-sensing is an active research area with numerous recent applications including tracking and monitoring the chronic health conditions of the patients [6], breath detection [22], fall detection [9] [34] [15], gesture [24] and even speech recognition [32] through fine tracking of lip movement.

Most prior work on physical activity tracking was focused on wearable devices such as smartphones [38], smartwatches [23], pedometers [3] or activity trackers [7]. Traditional activity trackers use accelerometer to recognise user activity and estimate calorie consumption based on personal details such as weight, height and age [14]. Research has been done into evaluating the accuracy of activity trackers [29], algorithm development, integration of sensors such as heart rate [28], novel hardware concepts, such as smart shoes [13]. More recent research investigates wearable devices to detect the initial symptoms and early signs of chronic conditions such as heart disease [30].

In this paper, we investigate an RF-sensing based approach for activity monitoring and energy expenditure estimation and evaluate its performance using real measurements. The proposed approach monitors received signal strength (RSSI) fluctuations resulting from user movements within an indoor environment and applies machine learning algorithms to classify user activity. The energy expenditure for each activity is then estimated based on its Metabolic Equivalent (MET) values and activity duration. The approach has been evaluated experimentally through a series of wireless measurements of various coarse-grained activities within a room using off-the-shelf IEEE 802.15.4 compatible transceivers. To the best of our knowledge this is the first study that proposes and investigates device-free RSSI-based method for human energy expenditure estimation.

The rest of the paper is structured as follows. Section III explains MET energy expenditure theory and the wireless sensing model used for measurements. Section IV focuses on the activity recognition using random forest and k-NN classifiers and the metrics used for evaluation. Section V presents experimental results and discussion. Section II describes related work on activity tracking and physical activity monitoring followed by a conclusion and future work in Section VI.

II. Related work

Activity recognition system is a vital component of future assisted living applications, which enables e-healthcare systems to recognise, monitor and track the health of the patients, detect falls, detect presence, and assist the elderly or disabled people with everyday tasks [26]. Thus, there is a significant amount of research on user activity recognition based on accelerometers, gyroscopes, video and other methods. While being popular and effective at estimating calorie consumption, wearable devices may not suitable for certain categories of patients due to the need for periodic maintenance [18] or other reasons.

In the early days, physical activity was assessed through self-reporting, which is a time-consuming and labour intensive process. Nowadays, device-based physical activity assessments became widely available and track activity based on either accelerometer, GPS, heart rate or multisensor technologies. A detailed review of various techniques in the context of health studies is described in [16]. In addition to specialised devices, there is also a significant market for general-use devices such smartwatches, smartphones or bracelets that estimate the energy expenditure based on a combination of accelerometer measurements and personal information about the user [4]. Smartphone based systems utilise built-in sensors to classify activities, such as walking, sitting or running. More recently, smartwatches became a promising platform for tracking not only calorie consumption or the number of steps but also the initial symptoms or early signs [30]. Apart from smartwatches, bracelets and smartphones, the researchers have experimented with novel concepts such as smart shoes [13], which can also be used for counting steps, activity and calorie estimation through gait analysis. However, it requires a user to wear a specialised equipment for sensing and data collection.

There is significant body of research investigating the accuracy of various physical activity tracking methods. For example, [17] proposed forecast models that utilised measurements from three on-body accelerometers placed on wrists, the hip and thigh. The model output was compared with the calorie expenditure as measured by metabolic analyser. [28] conducted a large scale study to evaluate the accuracy of several commercially available activity trackers in terms of heart rate and energy expenditure.

RF-sensing has emerged recently as a non-intrusive way to locate, track and recognise the activities of users without wearing any devices. The RF-sensing approaches use one of the following wireless signal features for activity recognition: received signal strength, channel state information or Doppler shift [33] [11]. The advantage of received-signal strength based methods is that it is supported by many off-the-shelf transceivers, and can be implemented using low-cost hardware. To the best of our knowledge, no prior work has investigated device-free human energy expenditure estimation.

III. System Model

A. Human Energy Expenditure model

Our energy expenditure approach uses Metabolic Equivalent Task (MET) concept, which represents a practical way of computing an energy cost of a human activity as a multiple of a Basal Metabolic Rate [2]. The concept is based on the fact that our cells utilise oxygen to facilitate the energy for fuel extraction, and the amount of oxygen a person inhales throughout activity is proportional to the amount of calories the body burns. One MET is defined as the amount of person's oxygen intake while at rest and is equivalent to 3.5 ml O2 per kilogram of body weight per minute, which is equivalent to 1.2 kCalories per minute for a 70 kg person. Therefore two METs represent twice the energy consumption compared to basal metabolic rate, and five METs represent the energy consumption five times the basal rate, and so on. The MET values for various household chores, sports and recreational activities are available through numerous studies in epidemiology [12] with some example values shown in Table I. The MET values in the table are from the most recent version Compendium of Physical Activities compiled to improve the comparability across the studies [2].

TABLE I
MET values for various activities

Activity Type	Metabolic Equivalent (MET)	Activity description
Resting	1.0	Inactively quiet
Sitting	1.3	At desk
Standing	1.8	Talking on phone/reading
Walking	2.0	Walking around the room

The basic expression for estimating total energy expenditure (TEE) in calories is [5]:

$$TEE = BMR \times MET \times TIME \tag{1}$$

Where TIME is an activity duration as a fraction of a day. Basal Metabolic Rate (BMR) is defined as energy required to maintain basic body functions for sustaining life such as breathing, nutrient processing, blood circulation and cell production. BMR depends on individual body metabolic levels and its accurate value is measured through direct or indirect calorimetry through measuring the amount of oxygen consumption or the amount of carbon monoxide produced by the body. However, a broad estimate of BMR can be computed based on sex, age, weight and age using Harris-Benedict equation [27]:

$$\begin{aligned} Men: BMR = 88.362 + 13.397 \times W + \\ +4.799 \times H - 5.677 \times A \end{aligned} \tag{2}$$

$$\begin{aligned} Women: BMR = 447.593 + 9.247 \times W + \\ +3.098 \times H - 4.330 \times A \end{aligned} \tag{3}$$

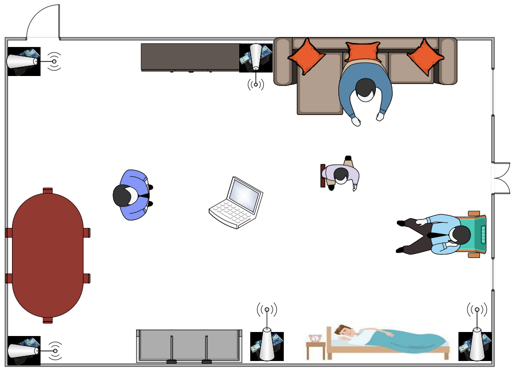

Fig. 1. The room layout and the location of wireless sensors and monitoring point in the room. The activity such as sitting and standing were performed in three different locations based on a typical user behaviour within that room, e.g. sitting either on an armchair, at the desk or on a sofa.

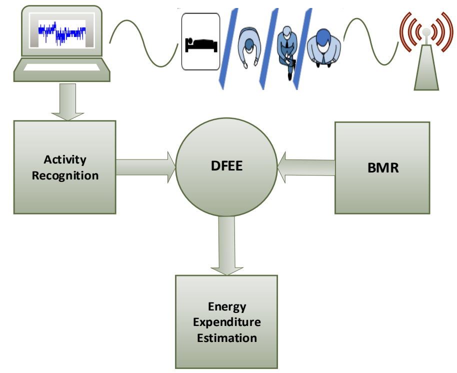

Fig. 2. An overview of activity recognition approach. The RSSI signal strength values are captures by the laptop and fed into a random forest classifier for activity recognition. The energy estimation is then based on looking up MET values for the predicted activity and multiplying that by an activity duration.

Where A, H and W represent age in years, height in centimetres and weight in kilograms respectively. As an example, a 31 year old male, with a weight and height of 70 kg and 165 cm respectively would have a BMR of 1642 kilocalories/day. An activity, such as household walking for 4 hours (MET = 2.0) would consume approximately $1642 \times 2.0 \times (4/24)$ = 547 kCal.

B. Wireless model

Our experiment environment consists of a room about 5 m×4.5 m size with 5 wireless sensor nodes. The nodes are equipped with a IEEE 802.15.4 CC2420 transceiver [1] operating in the 2.4 GHz frequency band. The 802.15.4 standard defines 16 channels, 5 MHz apart and 2 MHz of bandwidth, and uses Direct Sequence Spread Spectrum (DSSS) to map 4-bits data symbols to a 32-chip pseudo-random direct sequence, which is then modulated using offset quadrature phase shift keying (OQPSK). The nodes were programmed to transmit beacons once every second with a beacon interval randomised to reduce collisions. Each beacon contains information about sender ID, sequence number and all sender's neighbours together with their RSSI values, to monitor not only direct wireless links from nodes, but also the wireless links between the individual sensor nodes. The beacons are received and logged by a laptop equipped with a MTM-CM500-MSP base station located in the centre of the room. The transmitter output power was set to -10dBm to reduce effective range and minimise the impact of activities outside of the room on measurements. The data has been logged in the following format:

```
<timestamp> <sender ID><receiver ID><SEQ><RSSI>
...
```

Where SEQ is a beacon sequence number and RSSI is a signal strength respectively. The returned received signal strength values for CC2420 transceiver generally range from -100 dBm to 0 dBm with ± 3 dB linearity. The RSSI value is measured by the transceiver over approximately 128 μs, which corresponds to 8 symbol periods.

IV. Activity Recognition

An overall overview of a DFEE approach is presented in a block diagram in Figure 2. The raw RSSI data is preprocessed to obtain spatial RSSI signatures for each activity, which are fed into a Random Forest supervised machine learning algorithm as described in Section IV-B. Once the activity type is established, the energy expenditure is computed using the activity's Metabolic Equivalent.

A. Data pre-processing

As each wireless link generates a stream of RSSI values, a dataset represents a collection of multiple asynchronous streams, which are difficult to align with each other due to beacon randomisation, time synchronisation and occasionally lost packets. In order to extract RSSI signatures for each activity, the streams have been split into N-second epochs, with RSSI values for each wireless link replaced by their mean value within the epoch, which resulted in a sequence of tuples:

```
(EpochID, RSSI_1, RSSI_2, RSSI_i...RSSI_N)
...
```

Where i is a wireless link ID and N is the number of wireless links in the system. The other possible options for aggregating RSSI values is selecting either a minimum or maximum for each link within an epoch, however, selecting the mean showed the best performance as shown in the evaluation section later. Prior to classification, the aggregate RSSI values for each stream were then zero meaned and normalised by their standard deviation value.

B. Classifier algorithm

The classifier is responsible for mapping a spatial signature of signal strength values to a specific activity. The activity classification was done using Random Forest supervised machine learning algorithm, known for its high predictive accuracy and robustness to overfitting. Random Forest algorithm operates by constructing multiple decision trees from random subset of training data and computing an output class by majority vote

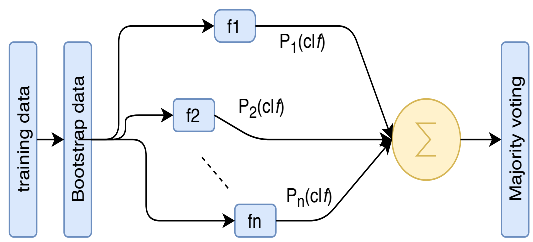

Fig. 3. Random Forest Classifier. The classifier constructs multiple decision trees from random subset of training data and computes an output class as a majority vote of individual tree predictions.

of individual tree predictions as illustrated in Figure 3. The parameters of the Random Forest classifier were selected to provide the best overall classification performance and Gini index estimates were utilized for choosing the best split.

In addition, k-nearest neighbour (k-NN) classifier was used as a baseline classification method. k-NN algorithm classifies a sample (in our case spatial signature) based on the majority voting of its k nearest neighbours. The algorithm is model-free, does not make any assumptions about the data and is one of the basic and robust machine learning algorithms. The optimal value of $k = 7$ was obtained based on the best model accuracy using 10-fold cross-validation as detailed in the experiment section.

C. Metrics

The classifier accuracy was measured using four metrics: accuracy, precision and recall which are defined below:

Accuracy: The metric shows the total proportion of data that has been correctly classified and is computed as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Where TP, FP, TN and FN refer to true positive, false positive, true negative and false negative respectively.

Precision: The metric shows the proportion of relevant (i.e. true positives) within the selected items and is defined as follows:

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

Recall: The metric also known as true positive rate or sensitivity, shows the proportion of relevant items that have been selected and is defined as follows:

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

V. Experimental Evaluation and Discussion

In this section we evaluate the proposed approach in terms of classification and overall energy expenditure estimation accuracy. The section also contains discussion on the performance and limitations of the approach.

A. Experiment setup

We have carried out the experiment by considering four different activities: sleeping, sitting, standing and walking. The activities were associated with various locations in the room that are typical for the activity [39]. Each experiment round consisted of a participant iterating through each activity spending a 10 minutes in each activity resulting in a 40-minute dataset. The measurements have been repeated 3 times resulting in a total of 120 minute of dataset. The participant of an experiment had the following parameters: height 165 cm, weight of 70 kg, male, aged 31 years old and was wearing Fitbit Blaze for comparison purposes. Fitbit Blaze is a popular device which has been evaluated for validity and reliability in previous studies [31]. A recording of a bracelet measurement was taken before and after each activity. The data has been processed using R statistical environment [25].

Fig. 4. Fitbit blaze used for validation.

B. Classification performance

The classification performance has been evaluated with 10-fold cross-validation, which consisted of splitting the data into 10 folds, and using one for testing and the remaining for training. This was repeated for each fold and the average results were taken. Table II compares the performance of selected classification algorithms in combination with the selected aggregate function. As can be seen a combination of a random forest with a mean aggregation function achieves the highest accuracy rate of 91.7%.

TABLE II
Classification accuracy comparison by classification algorithm and aggregation function

	Aggregation function		
Classification algorithm	mean,%	max,%	min,%
k-NN	86.7	79.2	79.0
Random Forest	91.7	82.9	82.5

TABLE III
Random Forest per-class classification performance

	Sleeping	Sitting	Standing	Walking
Recall	90.6	87.9	90.7	98
Precision	94	89	89	95
F1-score	92	88	90	97

Table III shows the performance of random forest classifier in terms of precision, recall, F1-score and accuracy. Most

TABLE IV
CONFUSION MATRIX FOR RANDOM FOREST CLASSIFIER

	sleeping	sitting	standing	walking
sleeping	26.7	1.2	0.9	0.7
sitting	0.9	21.7	1.6	0.5
standing	0.7	1.4	20.3	0.0
walking	0.2	0.2	0.0	23.0

TABLE V
COMPARISON OF DIFFERENT METHODS FOR ENERGY ESTIMATION

	TEE	DFEE	Fitbit blaze
Sleeping (10 minute)	11.4	11.8	11
Sitting (10 minute)	14.8	15.0	12
Standing (10 minute)	20.5	19.8	14
Walking (10 minute)	22.8	22.3	34

activities were classified reliably with walking, sleeping and standing classified most reliably with 97%, 92% and 90% F1-score rates respectively. A confusion matrix in Table IV shows real and predicted values in percentages averaged across resamples in columns and row respectively. As can be seen, sitting has the lowest classification rate and can occasionally be confused for sleeping or standing. Due to higher overall performance the rest of the statistics and discussion will focus on results obtained through Random Forest only.

C. Estimating Energy Expenditure

Based on activity classification results, the energy expenditure was estimated using MET values from the Compendium of Physical Activities [2]. DFEE energy expenditure is computed as a weighted average of energy cost of activities as recognised by the classification algorithm.

$$DFEE_i = \sum_{j=1}^{4} TEE_j * A_{ij} \tag{7}$$

Where TEE_i is a theoretical energy expenditure estimation based on ideal classification accuracy, and A_{ij} is a proportion of times that activity i has been classified as an activity j based on the confusion matrix. The DFEE values are compared with theoretical TEEs, as well as the measurements obtained from FitBit bracelet, Table V.

As can be seen the DFEE energy expenditure estimates are in close agreement with theoretical TEE values, due to relatively high classification rate with the discrepancy of 3.6%, 1.5%, 3.7% and 2.2% for sleeping, sitting and standing and walking respectively. Both DFEE and TEE overestimated the energy consumption for all activities except walking compared to FitBit. It is possible that the latter is using additional factors, such as pulse rate in addition to accelerometer data when estimating energy expenditure. The discrepancy between DFEE ranged from 7.4%, 25.4%, 41.2% and 34.4% for sleeping, sitting, walking and standing respectively.

D. Discussion

The achieved activity classification rate is higher compared to published results, which could be attributed to a number of factors. We used a full mesh topology by monitoring the wireless links between sensor nodes, compared to measuring RSSI over direct links between wireless stations and the laptop as in some previous studies on activity recognition. Using IEEE 802.15.4 sensor nodes has enabled monitoring of the wireless links bidirectionally, taking into account their asymmetric nature, especially in indoor environment. It is also possible that low power wireless links are more sensitive to user activity than Wi-Fi access points used in prior studies, which use relatively high power for signal transmissions.

The proposed approach focuses on single-person environments which can apply to environments such as small offices, elderly people living alone, or students living in their dormitories. In addition, monitoring people living in confined environments for a long duration of time, e.g. due to pandemic is another possible use-case. Unlike some smartwatches or bracelets, DFEE does not monitor heart rate levels or activity intensity when estimating energy expenditure. In this regard, our approach could be analogous to more traditional pedometers, which while providing a coarse-grained activity information, can measure an overall activity level of a person, but with the advantage of not having to wear any devices.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we describe a novel device-free activity human energy expenditure estimation approach and evaluate its performance through experiments. The method is based on using random forest classifier to analyse the wireless link fluctuations caused by human activity indoors to classify user activity and then estimating the energy expenditure using a Metabolic Equivalent concept from sport and dietary studies. The experimental evaluation has shown that the approach achieves a classification accuracy rate of up to 91.7% using a combination of random forest classifier with a mean aggregate function. The direct comparison with FitBit bracelet measurements and theoretical MET energy expenditure values have shown that the proposed DFEE estimates are within 7.4% to 41.2% for the experiments conducted in this study. The advantage of the proposed method however is that the user is not required to wear any devices.

Our approach is based on monitoring received signal strength measurements, a feature which is available on low-cost off-the-shelf transceivers. Extending the DFEE approach to take into account additional wireless signal information such as channel state information for more detailed activity recognition, as well as evaluation in wider range of physical environments is a potential future work.

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