Unsupervised Activity Clustering to Estimate Energy Expenditure with a Single Body Sensor

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***Abstract*—Body sensor networks (BSNs) have provided the opportunity to monitor energy expenditure (EE) in daily life and with that information help reduce sedentary behavior and ultimately improve human health. Current approaches for EE estimation using BSNs require tedious annotation of activity types and multiple body sensor nodes during data collection and high accuracy activity classifiers during post processing. These drawbacks impede deploying this technology in daily life -- the primary motivation of using BSNs to monitor EE.**

With the goal of achieving the highest EE estimation accuracy with the least invasiveness and data collection effort, this paper presents an *unsupervised*, *single-node* solution for data collection and activity *clustering*. Motivated by a previous finding that clusters of similar activities tend to have similar regression models for estimating EE, we apply unsupervised clustering to implicitly group activities with homogeneous features and generate specific regression models for each activity cluster without requiring manual annotation. The framework therefore does not require specific activity classification, hence eliminating activity type labels. With leave-one-subject-out cross-validation across 10 subjects, an RMSE of 0.96 kcal/min was achieved, which is comparable to the activity-specific model and improves upon a single regression model.

Keywords-Energy expenditure estimation; Automatition by unsupervised learning; ECG signals; Acceleration; Feature extraction; k-protopyte; PCA

I. INTRODUCTION

Reduced energy expenditure (EE) in sedentary lifestyle has been linked to the dramatic rise in obesity, Type II diabetes, and heart disease [1] in modern society. To study this epidemic and ultimately motivate expending more energy in daily life, accurately monitoring of EE for each individual is desired. However, current accurate EE assessment is still limited to expensive laboratory tools, which are often challenged by the ease of use, accessibility and portability [2] and therefore fail to meet the requirements for long-term, remote, personal EE monitoring.

Inspired by the wearability and continuous monitoring capability of body sensor networks (BSNs), significant research effort has been expended on estimating EE via BSN data. Inertial BSNs with accelerometers and/or gyroscopes are usually adopted, because EE is mostly correlated with mechanic energy generated by human bodies, and inertial sensors can directly capture motion intensity and patterns that are correlated to mechanic energy. How to best transform such data to EE, however, remains an open question, as the complexity and versatility of human motion challenge the effectiveness of analytical approaches and limit effective solutions to machine learning-based methods.

Most researchers have attempted to recognize specific activities accurately and assign Metabolic Equivalents (METs) derived from the compendium of activities to EE. These activity recognition approaches usually requires high classification accuracy to avoid diminishing accuracy of EE estimation with misclassification. Consequently, multiple inertial BSNs to capture motion intensity and motion patterns of multiple body segments and more specific annotations for activities during data collection are required for model training in machine learning. Moreover, the higher accuracy for detailed activity classification also implies more invasiveness and cumbersomeness by requiring more sensors worn on human body. These drawbacks further impede implementing this technology in daily life – the primary motivation of using BSNs for EE monitoring – limiting the current monitoring of EE to strictly controlled in-lab settings. In order for this method to work in daily life, an automatic approach for data collection without data annotation and with few body-worn sensors must be devised.

This paper addresses the abovementioned issues by bypassing specific activity recognition entirely. With the goal of achieving the highest EE estimation accuracy with the least invasiveness and data collection effort, this paper presents an *unsupervised*, *single-node* solution for data collection and activity *clustering*. Motivated by a previous finding that clusters of similar activities tend to have similar regression models for estimating EE [12], we apply unsupervised clustering to implicitly group activities with homogeneous features and generate specific regression models for each activity cluster without requiring manual annotation.

The rest of this paper is organized as follows. Section II reviews related work for standard tools in EE assessment in medicine and state of art activity recognition with inertial BSNs. Section III proposes the new framework for EE estimation, grouping data into homogeneous groups via unsupervised clustering before regression. Section IV details the experiment setup for data collection among 10 healthy subjects. Section V covers methodology adopted by the framework, elaborating the techniques for feature extraction, unsupervised clustering and regression for EE estimation. Section VI evaluates the results of using the model, compares with two prevailing methods, and discusses the advantage and limitations of this work. Section VII concludes and discusses the approach's impact and potential for real-world implementation.

II. Related Work

A. Standard Equipment in Medicine

Three kinds of gold standard tools exist for EE assessment: doubly labeled water, calorimeter room and circulatory calorimeter [14]. Doubly labeled water requires drinking of hydrogen isotope labeled water and is by far the most accurate method for assessing EE. However, it only outputs the total energy expenditure after an extended experiment period (e.g. 2 weeks) and does not provide information about frequency and intensity of the energy expended during certain activities [14]. A calorimeter room computes the total heat genesis of an enclosed room. However, it confines the subjects in a closed room for up to a day and has a delay in response up to 30 minutes [17]. Both of these two methods are costly, requiring dedicated laboratories and experts for data collection and analysis, rendering the monitoring less accessible in the real world.

The circulatory calorimeter takes a breath-by-breath record and computes minute-by-minute EE based on the amount of oxygen inspired and the amount of carbon dioxide expired using Weir's equation [13]. However, in addition to its cumbersomeness to wear, it requires a tedious calibration procedure to reduce errors resulting from maintenance [14], including room airflow calibration, following a double calibration, first with ambient air and then with calibration gas values. A delay calibration also needs to be performed weekly to adjust for the lag time that occurs between the expiratory flow measurement and the gas analyzers. These drawbacks inevitably hamper the circulatory calorimeter from monitoring EE in the real world.

B. Energy Expenditure with Accelerometers

Because of the close correlations between movement and EE, researchers have been trying to predict EE using movement features. Accelerometer-based BSNs are commonly used to capture movement features because of their availability and portable nature. With machine learning algorithms, researchers have attempted to transform the sensor data obtained from accelerometers into EE estimates. Two approaches have been applied in general. One directly estimates EE from accelerometer features [5][6][15] with regression models. The other recognizes activity types based on a pre-defined set of activities with pattern recognition and machine learning techniques, and then applies different activity-specific methods to derive EE [7][8][9].

Since activity type is identified as an important variable to predict EE, much research has focused on transforming accelerometer data to activity types (e.g. sitting, standing, walking, running, cycling, etc.) with pattern recognition techniques [3] and assigning static METs to the activities with compendium tables [18]. Such methods usually require at least three sensors to capture whole body motion in order to classify activities more specifically, introducing encumbrance in the data collection and processing. Also, classifying more activity types means more tedious annotations during data collection, reducing the feasibility of real-world implementation. Meanwhile, high accuracy in detailed activity recognition does not guarantee accurate EE estimation, since assigning static MET values to a specific activity type could not capture EE changes within an activity that are performed at different intensity levels [18]. EE estimation via detailed activity recognition is in essence a compression of the information from continuous time series to discrete activities types. In this process, the rich information contained in acceleration data per each individual subject during different activities is lost in generalized activity types and static MET values. Lastly, although a single regression method spares the labor of activity annotation, without activity recognition accelerometer features only reflect the local motion of the body segment where the accelerometer is mounted, disguising actual the activity intensity level that should be evaluated by whole body motion, thus providing less accuracy. In order to reduce the number of inertial sensors required while capturing the intensity levels, more direct indicators of EE – such as physiological signals – are to be explored for estimation.

Until recently, since the portable electrocardiography (ECG) sensors have become available, heart rate (HR) has been extracted from ECG sensor data to provide extra information for activity recognition. However, including such features in activity detection algorithms only improved the performance by 1-2% [9]. Nevertheless, the high correlation between HR and oxygen uptake can be explored [12] by involving HR as an important factor to predict EE via regression. One drawback of using only HR for regression though, is that the response delay in HR to physical activities often introduces prediction error for EE. For example, for a physically less fit subject, HR can remain high when he/she is at rest after a period of intense physical activities, leading to overestimation of EE since not as much energy is expended as a similar HR generated during exercising. Therefore, accelerometer features – which respond to motion change more promptly – must also be used as variables to estimate EE.

C. Cluster Acitivity Types and Energy Expenditure

[12] has explored the relation between physical activity patterns and EE and demonstrated that by applying different regression models for different clusters of activities, the estimation accuracy can be improved up to 20%. Without the hassle of classifying the motion signals to each specific activity, clustering them to six different levels is sufficient for the purpose of EE estimation. By incorporating the HR feature to differentiate different levels of EE, even without distinguishing the specific activities in each activity group, EE can still be estimated accurately. However, despite the efforts saved from annotating too specific activity types for classification [8], this approach still requires the annotation of a training set of the activity clusters. Nevertheless, results obtained when classifying clusters of activities [12] suggested that the activity groups are coarsely correlated with EE. In other words, there might be fundamental data structure residing in these clusters that possess homogeneity.

Therefore, we assume that clusters of activities represent similar data structures, and an automatic clustering solution grouping multi-attribute data into homogenous groups could lead to accurate EE estimation without specific activity recognition.

III. Framework

In this section, we propose a framework for extracting features from data, clustering the data into homogeneous groups, and generating regression models for accurate EE estimation. The process does not require activity labeling in data collection, as activity recognition is not required, hence the framework can automate the data collection procedure in the real world. We will also show that this method can be successful with the use of a single body-worn sensor node.

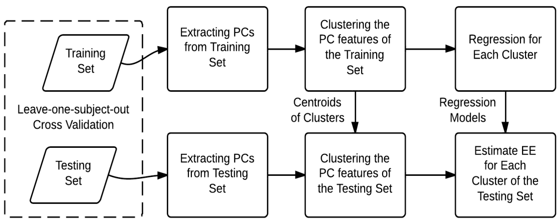


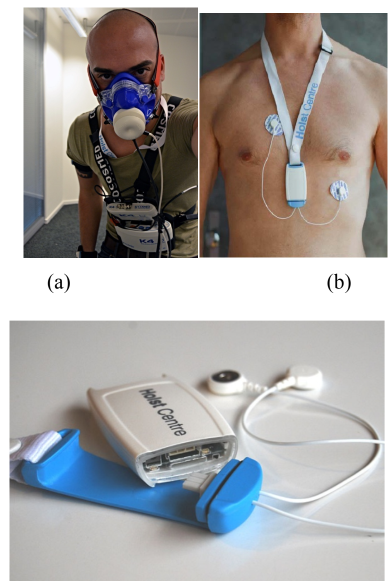
Figure 1. Flow chart of proposed method

Figure 1 illustrates the proposed framework as a flow chart. First the data is split into a training set and a testing set for leave-one-subject-out cross validation. Then Principal Components (PCs) are extracted from both the training set and testing set. The PCs of the training set are clustered via k-means clustering. The centroids of the clusters in the training set are used as starting points to cluster the testing set (also known as k-prototype method). For each cluster obtained in the training set, multiple linear regression models are generated using the circulatory calorimeter EE as output variables and the feature selected as input variables. Finally, to predict EE in the testing set, the models generated from training set are applied to each corresponding cluster in the testing set. The estimated EE and the ground truth EE of testing set data are compared in root mean square error (RMSE) for evaluation.

IV. Experimentation

10 healthy subjects with desk jobs from diverse ethnic backgrounds were recruited and agreed to a pre-defined data collection protocol, including refraining from drinking (except water), eating and smoking two hours before data collection. The data collection protocol consists of a wide range of sedentary and physical activities, which are conducted in two separated days, respectively. The sedentary activities were: *lying down, resting, sitting stretching, standing stretching, desk work, reading, writing, working on a PC, watching TV, fidgeting legs, standing still, standing preparing a salad, washing dishes, stacking groceries, folding clothes, cleaning the table, washing windows, sweeping, vacuuming, walking self-paced, walking self-paced carrying books (4.5 kg), climbing stairs up, climbing stairs down*. Each sedentary and household activity was carried out for a period ranging from 4 to 12 minutes, with a 1 or 2 minutes break between the activities. The data collection of physical activities were: *walking at 3, 4, 5 and 6 km/h on a treadmill, walking at 4 km/h carrying a weight (5% of the subject's weight), walking at 3 km/h, 5 and 10% inclination, walking at 5 km/h, 5 and 10% inclination, cycle ergometer at 60 and 80 rpm, low, medium and high resistance levels, running at 7, 8, 9 and 10 km/h*. Activities carried out at the gym were 4 minutes in duration, except for running, which lasted for 1 to 2 minutes. The total data collected aross10 subjects lasted about 20 hours.

During the data collection, the subjects were instrumented with a 1.5Kg indirect calorimeter (Cosmed K4b2 [16], shown in Figure 2 (a)) for validation purpose, and a 20 grams sensor patch developed at imec Holst Center on the chest (shown in Figure 2 (b)), consisting of one tri-axis accelerometer and an ECG sensor [4]. The integration of accelerometer and ECG sensor facilitates the fusion of the two types of sensor data in order to increase accuracy without introducing invasiveness (shown in Figure 2 (c)).



(a) (b)

(c)

Figure 2. (a) A subject is instrumented with circulatory calorimeter Cosmed K4b2 mask (b) A subject is instrumened with ECG+accelerometer patch (c) A close up of the ECG patch platform [4]

The indirect calorimeter was calibrated according to the manufacturer instructions and sampled at 0.25Hz. The ECG is sampled at 256Hz, and the accelerometer is sampled at 64Hz. The ECG data and accelerometer data were synchronized every 10 seconds via a wireless communication protocol to the computer clock during data collection. Both ECG data and accelerometer data are stored in a flash card on the sensor patch to ensure data integrity. The indirect calorimeter data and the ECG patch data (i.e. ECG and accelerometer data) were manually synchronized with post processing. Activity types were still labeled manually with a stopwatch during data collection in order to reproduce the evaluation detailed in [12] for model comparison. All data processing was done in MATLAB®.

V. ANALYSIS METHOD

This section elaborates the methods used to implement the framework introduced in Section III, including feature extraction from raw calorimeter data, ECG sensor data, and accelerometer data, clustering the data with k-prototype method after dimension reduction via PCA, and feature selection and regression method for each cluster.

A. Data Preparation and Feature Extraction

1) EE: respiratory data are acquired from the Comsed K4b2, which records the breath-by-breath volume of comsumption of O_2 and production of CO_2. EE was calculated based on Weir's equation [13]:

$$EE = (3.9 \times VO_2 + 1.11 \times VCO_2)/1000 \quad (1)$$

In equation (1), VO_2 is the oxgen consumed in milliliter, VCO_2 is the carbon dioxide produced in milliliter, and EE is the energy expended in kilo calories per minute (kcal/min). Missing data caused by noncontact moment of the face and the mask are first linear interpolated and then median filtered to remove the outliers in the EE data.

2) ECG sensor data: As heart rate is correlated with oxygen uptake [12], HR is extracted from ECG sensor data. A high-pass filter with a cutoff frequency at 4Hz is applied to remove the motion artifact superimposed in the ECG sensor signal, shown in Figure 3. Then HR is extracted from ECG data by counting peaks over 15 second windows then multiplied by four to get heart beats per minute. Additionally, the lowest HR was extracted from the HR data during lying down activity, and used to extract the heart rate above rest (HRaR):

$$HRaR = HR - mean(HR_{Lying}) \quad (2)$$

This feature captures better the relation of HR increment in response to physical activities and will be compared with HR feature in regression analysis.

3) Activity Labels: Activity labels are assigned to each data point (consisted of data in a 4s window) based on the activity list taken by stopwatch during data collection. This data is only used for model evaluation purposes.

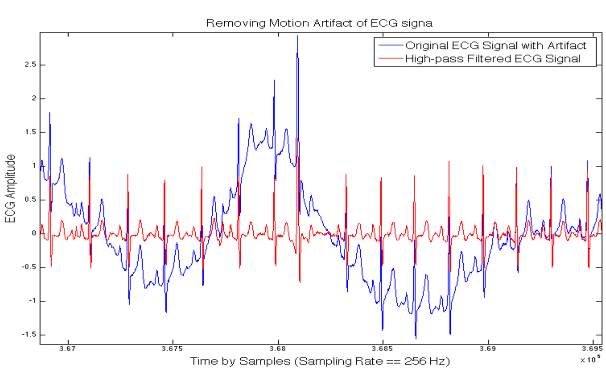


Figure 3. Removing motion artifacts from ECG signal using high-pass filter, the motion artifacts are superimposed in the orignial ECG signal

B. Dimension Reduction

Because 19 features in total are extracted from the accelerometer and ECG sensor node, dimension reduction was necessary to improve clustering performance. Since interpretability is not a concern for clustering, PCA transformation is selected for its effectiveness, and extracted PCs are used for clustering in the next step. Before extracting PC features, the accelerometer features are normalized to Z-score:

$$X_{normalized} = \frac{X - X_{mean}}{\sigma_X} \quad (3)$$

where X represents a feature vector extracted from accelerometer data, X_{mean} is the mean of the feature vector, and σ_X is the standard deviation of the feature vector .

C. K-Prototype Clustering

The K-means algorithm [24] aims to partition observations of multiple variables into k partitions based on the nearest mean. [11] has proven mathematically that k-means algorithm is equivalent to PCA, which "projects to the subspace where the global solution of k-means clustering lies, and thus facilitates k-means clustering to find the near optimal solutions". Therefore, clustering the PCs extracted from the original data set by the k-means algorithm can group data into homogeneous clusters for better regression models. To determine the number of clusters, k, a cross-validation based on the sum of distance criterion of k-means algorithm is conducted and sets k to be three.

The training set data is clustered by a classic k-means algorithm with initial centroids determined by iteration, the final centroids location and group index are saved as input for testing set clustering. To make sure the cluster in the training set has the similar structure as in the testing set, a variation of the k-means– k-prototype – is applied on the testing set data. After the training set is clustered, the centroids of the final clusters are recorded and used to initialize centroids of the testing set data. By using prototype of clusters (i.e. centroids) obtained from the training set, the testing set's clusters can be confined in the boundaries of the corresponding training set's clusters.

D. Feature Selection and Regression

Automatic feature selection algorithms were performed for choosing the predicting variables before building regression models. First, forward stepwise feature selection [23] was used to screen out the irrelevant features. Then a regularization technique — least absolute shrinkage and selection operator (LASSO) [22] — was used after stepwise feature selection to screen the selected features in order to avoid overfitting. The final feature set includes: HR (which captures physiological response to activities as it is directly related to respiration), variance and range of the absolute band-passed accelerometer data (which capture the intensity of body motion), zero crossing rate of z-axis accelerometer (which captures repetitive pattern of certain activities), and the weight of the subject to capture inter-subject differences on similar activities.

Without losing accuracy, multiple linear regression was chosen over other regression schemes such as random forest

[19], ensemble regression trees [20], multiple adaptive splines (MARS) [21], due to its simplicity for model interpretation and hardware implementation.

VI. Results and Discussion

The results of estimated EE for 10 subjects after cross validation is compared with ground truth EE (i.e. the circulatory calorimeter data) and evaluated by RMSE. To further evaluate the performance of the proposed method, two additional models were used for comparison: a single multi-linear regression model and an activity recognition based-model. The single multi-linear regression model uses the same set of features as the proposed model, while the activity recognition-based model is adopted from [12], which only requires recognition of six groups of activities and is evaluated at the perfect recognition accuracy. The results are presented in the form of box plot, illustrating the range, mean, and distribution of the RMSE (Figures 4-6).

Figure 4 presents the model comparison on data collected during both physical activities and sedentary activities, with the activity recognition model with ideal classification accuracy (i.e. assuming no misclassification). This ideal assumption provides the lower RMSE limit (0.84kcal/min) given the current setup. Although the real world implementation and misclassification decreases the final accuracy of EE estimation, the deterioration is slight, because the activities with similar EE being misclassified will not affect EE estimation much as found in [12]. Our proposed model achieves an RMSE of 0.96kcal/min, showing 12% improvement in estimation accuracy over the single regression model (RMSE of 1.09 kcal/min) and a lower accuracy compared to the activity specific model at the price of eliminating activity annotations.

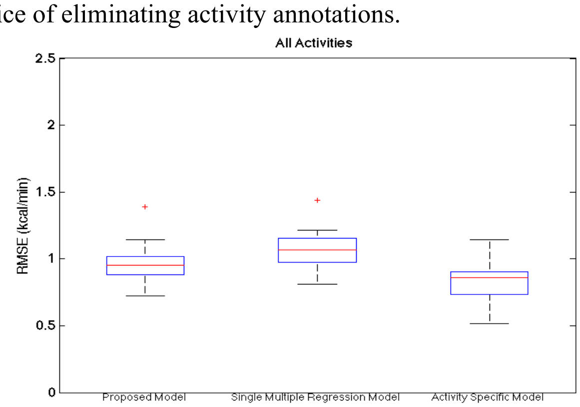


Figure 4. Model comparison of all activities

Because the range of EE of sedentary activities is naturally much lower than that of physical activities, the RMSE estimated for the former can be lower than the latter due to the lower range of EE. Also, monitoring EE of physical activities is more interesting than that of sedentary activities, since different sedentary activities do not vary in EE as much as different physical activities do and can be estimated as accurately by compendium tables as by using monitoring sensors. Given these issues, to fairly evaluate the models, sedentary activities and physical activities are separated based on the activity labels extracted from the annotations during data collection, as shown in Figures 5 and 6.

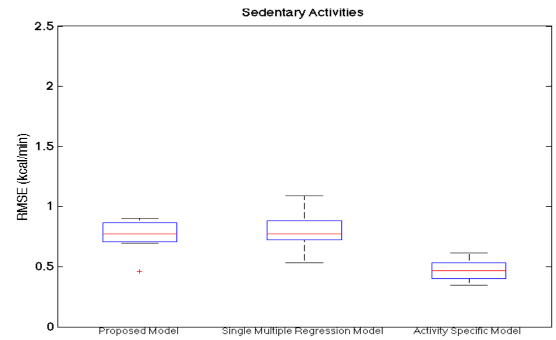


Figure 5. Model comparison of sedentary activities

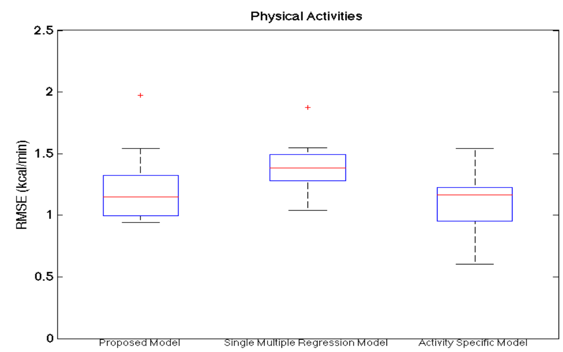


Figure 6. Model comparison of physical acitivities

For the EE estimation of sedentary activities (shown in Figure 5), the proposed model provides similar accuracy as the single regression model, though both provide poorer accuracy than the activity recognition based model with ideal classification accuracy. However, when evaluating the physical activities, the significant advantage of the proposed model is shown in Figure 6, where the RMSE of the single regression model increases to 1.38 kcal/min, while the proposed model has a comparable accuracy to the activity recognition based model (again, assuming 100% recognition accuracy). Overall, Figures 5 and 6 show that the proposed model has an advantage of reducing regression error of EE estimation in activities with larger variance (e.g. physical activities) by clustering the activities with similar sensor data characteristics.

Although the proposed method shows promising real-world implementation potential with the capability of automating data collection for accurate EE monitoring due to lack of a specific activity recognition step, it does not provide the knowledge of the relationships between activity types and EE. This can prevent the proposed method from further motivating the higher EE activities in sedentary life style via quantifying activity-dependent energy expenditure. We regard activity recognition as a parallel problem instead of a necessary intermediate step for accurate EE estimation. In other words, activity annotation, based on which activity types can be inferred, is only necessary for the purpose of studying the types.

VII. CONCLUSION

This paper explores the possibility of accurately estimating EE using a single body sensor patch (combining an ECG sensor and an accelerometer) with an activity recognition free approach. Driven by the goal of estimating EE more accurately without involving activity recognition in order to simplify the data collection procedure, a framework of combining unsupervised clustering and regression algorithms was designed for EE estimation. The ECG/accelerometer body sensor patch was used to collect data on 10 subjects during physical activities and sedentary activities, with circulatory calorimeter recorded EE providing the ground truth. Validated by leave-one-subject-out cross validation, an RMSE of 0.96 kcal/min was achieved using the proposed model, comparable to the activity specific model (wither perfect activity classification accuracy) and improving upon the single regression model by 12%. Overall, despite lacking specific activity type information, the proposed model shows the potential for implementing accurate EE monitoring in the real world with portable, automated data collection.

In the future, other unsupervised clustering algorithms will be investigated to improve grouping of heterogeneous data sets and the final accuracy of EE estimation. Interpretation of clusters after unsupervised clustering will also be studied to find the relationship between clustered activity types and EE. With a simple rule based classification algorithm, sedentary activities and physical activities can be separated in real-time, enabling the monitoring of only physical activities in order to save battery life. Finally, the multiple linear regression models will be implemented and tested in real-time, demonstrating the possibility of EE monitoring in real world.

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