Constructing Energy Expenditure Regression Model using Heart Rate with Reduced Training Time

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***Abstract*— Accurate estimation of energy expenditure (EE) is a key enabler for many applications of healthcare and wellness. Heart rate (HR) based EE estimation methods typically require extensive training time to establish a relationship between HR and EE. In this work, we propose a method where just the few most representative EE-HR data pairs are used to train the estimation model. Furthermore, we present a systematical methodology based on the ranking of the correlation coefficients between EE and HR to find the least amount of EE-HR data pairs required for training while satisfying the constraint of estimation accuracy. During the experimental evaluation, while the study participants walk and run on a treadmill, our method is compared to three different training paradigms: training the EE-HR model 1) using all available data collected during the experiment, 2) using the EE-HR data only during speed changes (or during monotonic HR changes) and 3) using the EE-HR data pairs collected during constant speed. The results show that our method could maintain a comparable EE estimation performance as shown by only 2~4% changes on the coefficient of variation of root-mean-squared error (CV(RMSE)) for the testing dataset while saving nearly 91-97% training time for each individual.**

I. INTRODUCTION

Inactive or less active lifestyles have become a major challenge among nearly two thirds of the total world population, leading to overweight, which in turn is one of the primary reasons for diabetes and many other disorders. Monitoring of energy expenditure (EE) for habitual activities, apart from sedentary time, can be crucial to maintain a healthy lifestyle. The accuracy of energy expenditure estimation must be good enough to be able to verify the required small differences between daily energy intake and energy expenditure (*e.g.*, 500 kcal daily energy deficit for monthly weight loss of 4 lbs) [1]. A commonly accepted method for accurate EE monitoring is to use a computer-based stationary system to measure the oxygen consumption (VO2), an indirect estimate of EE. However, such a measurement method is inconvenient and cumbersome for 24-hour monitoring [2]. Alternatively, EE estimation based on motion detection is durable, portable and affordable, at the expense of relatively larger EE estimation error (20-35%), *e.g.*, EE estimation based on counting steps taken. Estimation based on more intensive motion applications such as rowing and cycling have shown even larger error [3].

An alternative is EE estimation based on heart rate, which is a highly-correlated physiological parameter reflecting EE regardless of activity patterns; EE estimation is relatively accurate in steady conditions like sitting or slow indoor walking when the contact between the HR sensors (*e.g.*, electrocardiogram or photoplethysmogram sensors) and the skin is stable. Therefore, a wearable device with heart rate monitoring capability is a practical candidate for relatively accurate and suitable 24-hour EE estimation and monitoring. It is important to note that the EE monitoring is usually more meaningful during exercises, however, most of the regression-based models relating EE to HR show relatively large errors, which is possibly due to the natural fluctuations in HR during the relatively stable EE [4]. Therefore, the selection of *suitable* data for the regression model training could be one potential approach to enhance the training performance. Another obstacle in realizing the practical EE estimation stems from the fact that extensive calibration time is needed for each individual to adjust the predefined regression model to best fit the gold standard EE since no pre-defined guideline is available for effective calibration. Most of the previous studies build the regression model by simply using as much data as they can which lead to less than ideal and in cases poor performance [5]. For example, the calibration test to determine the EE-HR relationship takes a minimum of 45 minutes per subject, let alone subsequent processing of this data which is also time consuming [6]. Therefore, a well-defined experimental design and corresponding data selection algorithm will be beneficial to the reduction of calibration time and maintaining or enhancing the accuracy of the training model.

In our work, we observed that the most-correlated EE-HR data pairs collected during the speed-change region is of essential importance for the regression model training. We propose a systematic method to find those most representative EE-HR data pairs and evaluate its efficiency. The experimental results show that our method leads to significant training time reduction while maintaining comparable estimation accuracy and performance.

A large number of wearable devices have been used to estimate EE from movements and physical activities. Some methods directly use accelerometers combined with gyroscopes to estimate EE [7]. Some researchers believe the relationship between EE and HR differs in various activities and therefore, more sophisticated algorithms like hidden Markov models (HMM) and artificial neural networks (ANN) are used to classify activities before the EE estimation [8]. However, movements are not directly related to metabolism, since the movement type and conditions influence the estimation, and movement based methods cannot generally describe reliably the intensity of physical activity [9].

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Moreover, choosing the body locations for sensors placement to estimate EE is very important but challenging. For instance, a traditional waist-worn sensor is highly inaccurate for monitoring EE during riding a bicycle.

Research studies have also shown that HR monitoring is a feasible technique for estimating EE [10]. Furthermore, it has been proven that the linear relationship between HR and EE varies among subjects [11]. Some groups perform activity recognition over a pre-defined set of activities, and then apply combinational multi-dimensional regression method to predict EE based on the HR and acceleration [12]. For the best accuracy, individual laboratory training of the EE-HR relationship is necessary.

Our method has its roots in HR-based EE estimation, but focuses on data selection for the regression model training with an expectation of reducing as much training time as possible for each individual while maintaining a comparable estimation performance.

II. METHODS

HR data is mostly significant during speed changes as the EE varies. When the speed remains constant, the HR and EE remain relatively consistent. This will be illustrated later in this manuscript. Our method to select the most correlated EE-HR data pairs when the speed changes. This process can be divided into two steps. Firstly, we use accelerometer data to monitor the speed change time region and choose the corresponding EE-HR pairs. Secondly, most-correlated EE-HR data pairs are obtained by correlation-based segment ranking calculation on the previous selected data which will be described in Subsection III.B.

A. *Detection of Speed abrupt Changing Samples*

Three-axis accelerometers can be used to monitor the speed changes by tracking the principal frequencies in the power spectral density of the accelerometer stream. Speed variations along with the HR changes are shown in Fig. 1. The monotonic change region of HR also reflects the abrupt speed transition but with a slightly wider time span due to the time taken for heart to adjust to the speed and activity intensity changes and the need to pump more blood. The time span corresponding to the speed changes for the regression is defined as the time interval centered on the sample where exact speed change happens, with a span of 10 seconds on both sides. This time duration is often somewhat short and is not very visible in Fig. 1 although they can be noticed with sufficient attention.

B. *Correlation-based Segment Ranking*

Within the time segments, where the running speed is changing, it is observed that the EE-HR pairs contribute differently to the regression model. The reason could be multi-fold. The first cause is short term physiological random fluctuation of EE and HR within these regions. Secondly, there are uncertainty and noise associated with EE and HR measurement devices. Finally, motion artifact during running will bring random distortion to the signal. Therefore, we applied an algorithm to automatically select EE-HR pair with the best correlation and with an expectation that those well-selected training data will lead to superior performance while reducing the training time.

At first, we divided all EE-HR data pairs inside these areas into different segments. After we evaluated each segment based on the Pearson product-moment correlation coefficient between HR and EE, as shown in (1):

$$\rho^i_{X,Y} = \frac{E[(X^i - \mu^i_X)(Y^i - \mu^i_Y)]}{\sigma^i_X \sigma^i_Y} \tag{1}$$

where X^i and Y^i are HR and EE samples acquired from chest worn ECG and integrated metabolic system (gold standard) in the i^{th} segment, μ^i_X , μ^i_Y and σ^i_X , σ^i_Y are the mean and standard deviation of X^i and Y^i, respectively and the resultant $\rho^i_{X,Y}$ is in the range of [-1,1].

Secondly, the correlation coefficients for all the segments are ranked in a descending order as shown in (2).

$$Index = Ranking_i(\rho^i_{X,Y}) \tag{2}$$

The final data pairs are selected by thresholding as shown in (3).

$$Index_{selected} = \{\rho_{X,Y}{}^{i}_{Index} > Thresh\} \tag{3}$$

Thereafter, those selected points specified by $Index_{selected}$ could be used for training the linear regression model as in (4).

$$EE = a * HR + b \tag{4}$$

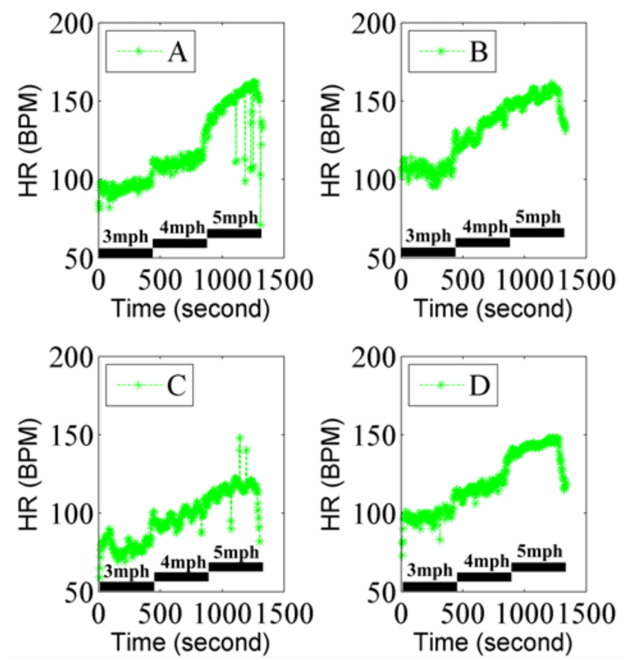

Figure 1. HR (BPM) over time and 3 speed segments detected for subjects A, B, C, D

III. EXPERIMENTS

A. *Lab Test Description*

The ground truth EE was measured using Parvo Medics' TrueOne system together with a Cardiac Science TM65 treadmill. The accuracy is 0.1% for 0-10% CO_2. Gas flow was measured by a Rudolph heated pneumotach.

The lab, during our experiment, was kept at constant room temperature (21ºC). HR was measured using a Polar chest belt. Additionally, one 3-axis accelerometer sensor was attached to the wrist of subjects to monitor the running speed.

B. *Test Protocols*

The treadmill test was manually controlled. We collected data for each of the four subjects, at speeds of 3 mph, 4 mph and 5 mph. The duration of data collection session for each of the three speeds was 7 minutes. The switching time between two consecutive speeds was 2 seconds.

C. *Subjects Characteristics*

Four healthy male subjects were selected for the purpose of our test. The subjects had different heights and weights. Their physical characteristics are listed in Table I.

TABLE I. CHARACTERISTICS OF SUBJECTS

Subject	**Age**	**Height (in)**	**Weight (lb)**
A	22	76	195
B	23	64	148
C	25	71	175
D	25	72	207

The Institutional Review Board at University of Texas at Arlington approved the study, and all subjects signed informed consent forms.

IV. RESULTS AND DISCUSSIONS

With all the training data points (EE-HR pairs) used as input, a linear regression model is obtained for each subject. Fig. 2 clearly demonstrates a linear relationship exists between EE and HR for all the subjects, across all three running speeds. We put all the training and testing data together for each subject.

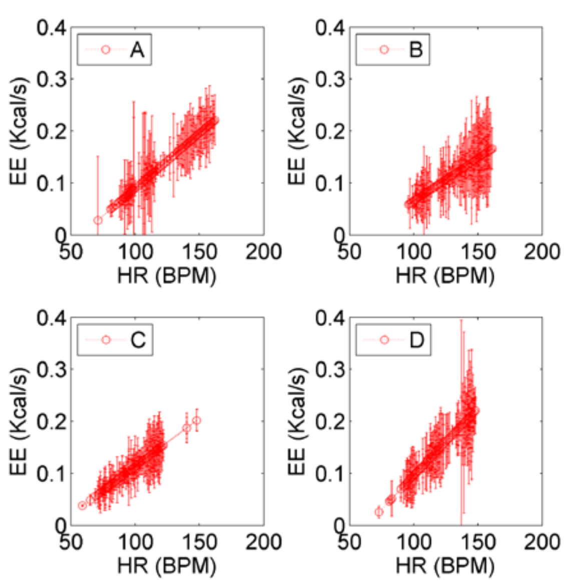

Figure 2. Illustration of the linear relationship between EE and HR for 4 subjects

For training the regression model, four different cases are considered: Case 1) using all EE-HR data pairs regardless of running speed, Case 2) all EE-HR data pairs during constant running speeds, Case 3) all EE-HR data pairs during speed changes and Case 4 (our method)) the selected EE-HR data pairs by our proposed correlation based method.

By implementing our correlation coefficient based ranking method for all the segments of EE-HR data pairs during speed changes, we performed a simple test to validate that merely a few most-correlated EE-HR data pairs are sufficient to construct an accurate regression model, which is shown in Fig. 3. The figure shows that the RMSE of the regression model begins to stabilize after adding a few data pairs. The RMSE is calculated using the test data. The total number of samples considered is the number of EE-HR pairs during the transitional regions (speed changes). The number of pairs is directly sampled in the transition region when we experience speed changes as shown in Fig. 1 with the number of samples ranging from 44-60 for each subject. In a practical application, the threshold on the correlation coefficient could be decided based on trial and error to determine the most-correlated EE-HR data pairs.

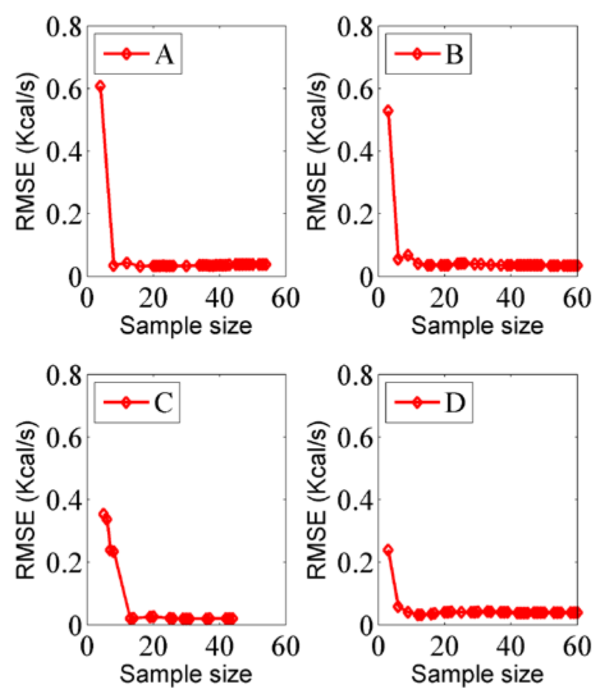

Figure 3. RMSE on the testing dataset over increasing training sample size-correlated EE-HR data pairs on 4 subjects

For each subject, Fig. 4 shows the two regression models constructed using all EE-HR data pairs and using only our selected EE-HR data pairs, respectively.

For all subjects, the raw EE-HR pairs are very noisy with a large deviation. The regression results with our selected EE-HR pair data agrees well with the results for all EE-HR data pairs while showing a minor deviation.

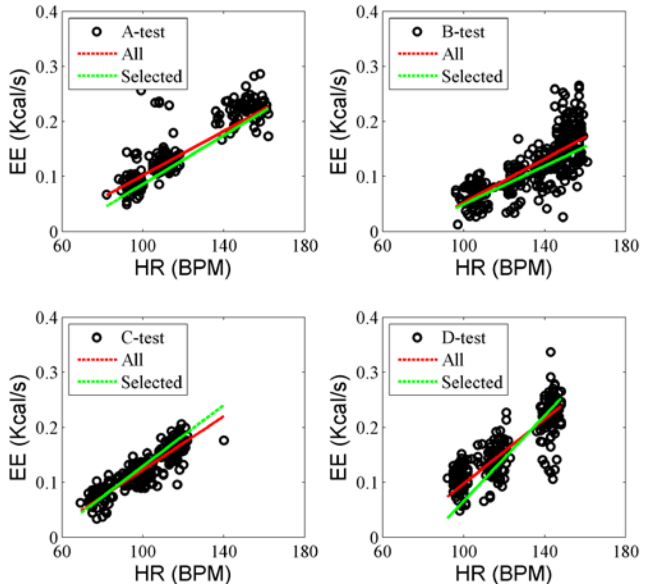

Figure 4. Comparison of two regression models built from all EE-HR data pairs and selected EE-HR data pairs (Black circles: All EE-HR pair data. Red line: All pair Green line: selected pair regression result)

In Table II, we show the regression performance by the coefficient of variation of the RMSE (CV(RMSE)) and the training time by number of samples for four cases. The CV(RMSE) is defined in (5), where y_t, $\hat{y}_t$ are the true and estimated EE respectively, $\bar{y}$ is the mean of y_t, and n is the total number of test data.

$$CV(RMSE) = \frac{\sqrt{\frac{\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}{n}}}{\bar{y}} \qquad (5)$$

TABLE II. THE RESULT OF EE ESTIMATION PERFORMANCE AND TRAINING TIME OVER FOUR TRAINING DATASET CASES [c]

		Subject			
		A	***B***	***C***	***D***
Case 1	CV(RMSE)	0.19	0.28	0.28	0.19
	Sample Size	245	384	282	289
Case 2	CV(RMSE)	0.18	0.28	0.28	0.19
	Sample Size	191	324	238	229
Case 3	CV(RMSE)	0.39	0.32	0.32	0.18
	Sample Size	54	60	44	60
Case 4 - our method	CV(RMSE)	0.22	0.3	0.3	0.23
	Sample Size	22	20	13	9
Case 4 vs. 1[d]	CV(RMSE)[a]	0.03	0.02	0.02	0.04
	Sample Size reduction [b]	0.91	0.95	0.95	0.97

a) Difference CV(RMSE) for Case 4 relative to Case 1.

b) Sample size reduction for Case 4 relative to Case 1.

c) Case 1: all EE-HR data pairs. Case 2: Data pairs from constant speed. Case 3: Data pairs from when speed changes. Case 4 - our method: selected data pairs from Case 3

d) Selected versus 1: relative changes for Δ CV(RMSE) and sample size reduction between Cases 4 and 1

The results show that the sample size (and training time) using our method can be reduced by more than one order of magnitude compared to Cases 1 and 2 and significantly compared with Case 3 (4X reduction) while the regression model maintains a comparable accuracy. It is also important to note that the accuracy of the regression model leveraging our technique is better than Case 3.

V. Conclusion

An HR-based EE regression model training efficiency based on selected samples was investigated. Experiments on four human subjects on a treadmill with speeds of 3 mph, 4 mph and 5 mph were carried out. Samples with the most-correlated EE-HR data pairs from the speed transitional region observed to be the best candidates for constructing the regression model. The regression results showed only 2~4% changes on the coefficient of variation of root-mean-squared error (CV(RMSE)) while saving nearly 91-97% training time for each individual. Our methods along with the test procedures are proved to be very effective to model the EE-HR relationship.

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