EPOC aware Energy Expenditure Estimation with Machine Learning

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***Abstract*—In 2014, 39 % of adults were overweight, and 13 % were obese. Clearly, knowing exact energy expenditure (EE) is important for sports training and weight control. Furthermore, excess post-exercise oxygen consumption (EPOC) must be included in the total EE. This paper presents a machine learning-based EE estimation approach with EPOC for aerobic exercise using a heart rate sensor. On a dataset acquired from 33 subjects, we apply machine learning algorithms using Weka machine learning toolkit. We could achieve 0.88 correlation and 0.23 kcal/min root mean square error (RMSE) with linear regression. The proposed model could be applied to various wearable devices such as a smartwatch.**

***Index Terms*—EPOC, energy expenditure estimation, machine learning, exercise, application, healthcare.**

I. Introduction

Physical exercise is important for keeping fit. Frequent and regular physical exercise boosts the immune system and helps prevent the diseases such as heart disease and obesity [1]. Obesity is an epidemic all around the world. Worldwide obesity has more than doubled since 1980. In 2014, 39 % of adults aged 18 years and older were overweight, and 13 % were obese [2]. This health crisis is growing because of poor dietary habits and the lack of physical activities. Raised body mass index (BMI) is a major risk factor for noncommunicable diseases such as cardiovascular diseases, diabetes, musculoskeletal disorders, and some cancers [2]. To prevent obesity, people can engage in regular physical activity. Indeed, 150 minutes per week are recommended for adults [2].

People keep wondering about the amount of energy used for exercises. To simply estimate the amount of exercise, they use a calorie consumption as an indicator of the amount of working. However, it is extremely hard to know the exact calorie consumption for exercise. A calorie consumption displayed on the exercise equipment in the gym is in general inaccurate because of the simple energy modeling and calculations. Knowing exact calorie consumption, i.e., energy expenditure is important for sports training, weight control [3]. This is true in healthy humans and during acute illness, where reduced EE may be related to the fatal outcome [4]. The excessive exercise raises the possibility that more extreme exercise may have some detrimental effects [5]. Therefore, there is a need of tools to accurately tell how much exercise people did in a quantitative manner. Furthermore, provision of tools to accurately measure EE would allow people to actively track expenditure of calories, creating awareness of personal habits that can be modified to promote personal health.

An energy expenditure commonly means the expenditure of energy during exercise. But, excess post-exercise oxygen consumption must be included in total energy expenditure to know exact one [6]. During exercise, there is an increase in oxygen uptake to support the increased energy need. After exercise, oxygen uptake does not return to resting levels immediately, but may be elevated above resting levels for some periods of time [7]. Therefore, EPOC can help you burn more calories long after you have left the gym. Furthermore, high-intensity interval training burns more calories than low-intensity and continuous exercise for the same period of time because high-intensity workouts can increase VO_2 max (maximal oxygen comsumption), i.e., the ability to use oxygen for energy [8].

Several techniques have been proposed for EE estimations since EE is significantly important for the accurate amount of exercise. Researchers have investigated EE estimations during exercise by using wearable sensors such as accelerometer and barometer [9] [10] [11]. They proposed simple regression models and estimation formula. However, they ignored important individual characteristics such as gender, age, height, weight, and BMI to estimate EE for exercise [10]. Further, they did not consider EPOC which is again significantly important for EE estimations. Interestingly, researchers have presented machine learning-based estimations for achieving a high accuracy in terms of EE [12]. Some machine learning-based techniques even considered individual characteristics. However, they collected a small amount of data relatively and disregarded EPOC effect which takes up an important part of EE [13]. Recently, Rusko et al. investigated EPOC effect during exercise [14]. However, their evaluations have shown a relatively low correlation, 0.42, between predicted value and ground truth one.

Definitely, there is a necessity of a machine learning-based approach considering EPOC effects and individual characteristics as well for accurately and effectively estimating EE. Our machine learning-based approach is quite effective with lots of data which reflect individual characteristics on EE estimations

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and thus accurately estimate EE. Further, we exploit a heart rate sensor because the heart rate is closely related to the EE [15]. In this paper, we present machine learning-based EE estimations with individual characteristics on 33 different subjects during and after aerobic exercise. Consequently, our machine learning-based approach has shown the efficacy as compared to existing techniques and our experimental results have delivered 0.88 correlation and 0.23 RMSE.

The main contributions of this paper are as follows:

- We propose a method that practically offers energy expenditure both during aerobic exercise and after exercise, EPOC, using heart rate sensor.
- We apply a machine learning-based approach to estimate EE with individual characteristics for accuracy.
- Our method could be applied to off-the-shelf wearable devices such as a smartwatch.

This paper presents a novel method, which accurately estimates the EE during exercise and after exercise using machine learning-based approach with a heart rate sensor.

II. Related work

Researchers have investigated the energy expenditure estimate across various activities using wearable sensors. Accelerometer is the most popular among sensors in EE estimation. On the one hand, most of them presented various linear regression models and applied the Compendium of Physical Activities [16] for EE estimates. On the other hand, Voleno et al. [10] evaluated the usefulness of a barometer with accelerometers to accurately estimate the subject EE of the complex activities such as stair-up and stair-down. For example, previous EE models resulted in the RMSE by 2.12 kcal/min [10] and 1.19 kcal/min [11]. However, these simple energy estimates are insufficient to obtain accurate information mainly because they miss the individual characteristics and ignore the EE after the exercise, i.e., EPOC [17] or afterburn. Each individual consumes the different amount of calories and continues burning the calorie after the exercise, i.e., EPOC.

Interestingly, a few recent works have investigated machine learning-based approaches for EE estimation. Pande et al. [12] applied artificial neural networks [18] to accumulated data and built classifiers with training data for EE estimates. They exploited machine learning-based techniques to obtain the high accuracy with the least error. Although the machine learning algorithm is computationally expensive in training phase, its complexity is very low for testing and practical phase. They utilized affordable smartphone sensors such as an accelerometer and barometer to accurately estimate EE for four ambulatory activities, e.g., walking, standing, stair-up, and stair-down. Their machine learning-based models demonstrated up to 0.89 correlation with actual EE, and the RMSE by 1.07 kcal/min. However, they collected a small amount of data in a short period of time and left out of consideration in the value of EPOC for the complete EE estimation.

Whole-body energy expenditure is accounted for by oxygen uptake during and after exercise [6]. To achieve the accurate and complete EE estimates, we need to consider post-exercise effects, i.e., EPOC for EE estimates. EPOC also can help us achieve the optimal level of calories burning from workouts. It is enabled to develop an appropriate exercise plan by adjusting the duration of the exercise. Since the widely used formula for EPOC calculations has not been presented, we need practical methods for EE estimates with the EPOC values. The most accurate method for EPOC estimates is to use direct or indirect calorimeters such as COSMED K4b2 calorimeter [19]. However, direct or indirect apparatus is impractical for use in daily life because of the high cost, complexity, and difficulty of use [19]. So far, the machine learning-based approach has not been applied to accurately estimate the EPOC. On the other hand, different research trends of EPOC are to find the factors influencing EPOC in a limited manner. For example, high-intensity interval training is the most effective method to stimulate the EPOC effect [20].

III. Our machine learning-based approach

We explain why we choose the machine learning-based approach. Because we obtain heart rate values during 7 hours per subject from 33 subjects participated in our experiments, we can acquire a large amount of data for estimating EE. The machine learning-based approaches are generally exploited to appropriately cover a large amount of data and to implement a data-centered process to estimate [21]. Consequently, we apply the machine learning-based approach for estimating EE.

Currently, smart devices include embedded heart rate sensor. Heart rate sensor is very easy to use on commercial devices such as smartphones. Heart rate sensor is selected to closely approximate EE compared with gold-standard EE. It is because heart rate is related to the EE [15]. It is possible to estimate physical activity energy expenditure from heart rate in a group of individuals with a great deal of accuracy [22].

Our approach exploits machine learning-based approaches to obtain high accuracy of EE estimation. Three steps for EE estimation are applied to our approach as shown in Figure 1. First, data collection phase collects the heart rate sensor data and adjusts the data, i.e., preprocessing to remove outliers for machine learning. Second, feature extraction phase calculates feature vectors using heart rate values and individual characteristics for machine learning. Lastly, datasets consisted of feature vectors is applied to machine learning algorithms as input values utilizing Weka machine learning toolkit [24].

A. Data Collection

Our experiments require us to collect the raw heart rate sensor data and individual characteristics from 33 healthy subjects. Individual characteristics such as gender, age, height, weight, and BMI from subject participated in our experiments are collected using a height and weight scale. The heart rate is sampled for 20-min aerobic exercise and 3-hour rest using Polar heart rate monitor [23]. The Polar heart rate sensor is sampled at a frequency of 1/60 Hz. Therefore, 200 heart rate samples in bpm per subject are collected during and after exercise. Although the sensor data is recorded on the

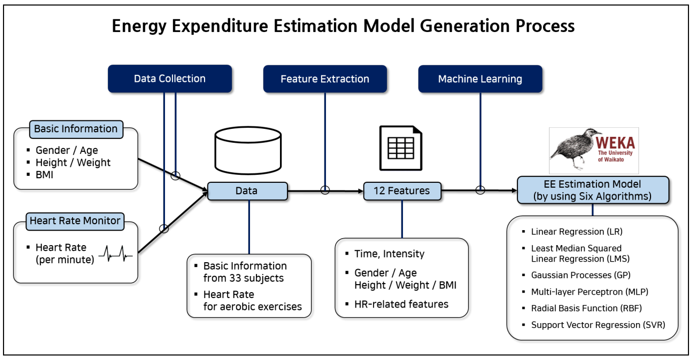

Fig. 1. The process for generating EE estimation models

computer and is computed offline for analysis purposes, our system also could run in real-time on smart devices. The gold-standard of energy expenditure is acquired using an indirect calorimeter, i.e., the automatic gas analyzer. Breath-by-breath gas exchanges can be converted into an energy expenditure. Therefore, we compare our estimated energy to a ground truth acquired from the automatic gas analyzer.

B. Feature Extraction

We extract three types of features for applying machine learning. The features are divided into standard setting for machine learning, individual characteristics, and the representative value of heart rate sensor. EE is influenced by individual characteristics and heart rate. Therefore, we extract the value as feature for machine learning.

We obtain features for standard setting.

- *Time*: exercise duration in *min*
- *Int*: exercise intensity (40 % or 70 % of the maximum)

We extract individual characteristics as feature vector.

- *Gen*: gender of the subject
- *Age*: age of the subject in *year*
- *Hei*: height of the subject in *cm*
- *Wei*: weight of the subject in *kg*
- *BMI*: BMI of the subject, calculated by dividing the weight with the square of height and measured in kg/m^2

And heart rate features in bpm are calculated.

- *HRmax*: maximum heart rate during exercise
- *HRmed*: median heart rate during exercise
- *HRavg*: averaged heart rate
- *HRstd*: standard deviation
- *HRint*: exercise intensity acquired from heart rate

C. Machine Learning

In prior phase, we generate datasets comprised of 12 features for applying the machine learning. Training data and testing data are organized by using 10-fold cross validation. We need to choose appropriate algorithms which can apply our sensor data. We select 6 algorithms because they enable the numeric data as an input data to implement the machine learning. Especially, the machine learning algorithms could be portably applied on Weka toolkit. We implement the Weka toolkit for applying regression algorithms such as a linear regression (LR), a least median squared linear regression (LMS), Gaussian processes (GP), a multi-layer perceptron (MLP), i.e., an artificial neural network, a radial basis function network (RBF), and a support vector regression (SVR).

D. Performance Metric

The performance of EE model is evaluated using the RMSE (1) from the gold-standard value, since it is the most commonly used metric in the EE estimation domain [3]. The additional metric of Pearson correlation coefficient (2) is also employed to measure the linear correlation between estimated energy value and true energy value. Lastly, the relative error (3) is calculated for a special case of the percentage form of relative change. They are defined as follows:

$$RMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X-Y)^2}}{time} \tag{1}$$

$$Correlation = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \tag{2}$$

$$RelativeError(\%) = \frac{|X-Y|}{Y} \cdot 100 \tag{3}$$

where *N* is the number of the instances, *X* is the estimated EE and *Y* is the ground truth EE, *time* is the exercise duration, σ is the standard deviation, μ is the mean, and *E* is the expectation.

IV. Evaluation

A. Experimental setup

Thirty-three healthy subjects (21 male, 12 female) aged 19-41 years are recruited from the Yonsei University to participate in this study. Table I shows the distribution of the 33 subjects. Subjects sign on informed consent form. They are required to participate on an empty stomach for 8 hours. Prior to the main treadmill scenario, we check the individual physical statement to design an experiment. Subjects are scheduled on different days to perform one or both of the two different 20-min scenarios, scenario 1 at the 70 % of maximal test condition and scenario 2 at the 40 % of maximal test condition, while wearing a heart rate sensor at the chest, a indirect calorimeter. Detailed scenarios are listed in Table II. Exercise type is configured quickly walking or running on a treadmill with aerobic exercise. We monitor the heart rate of the subject during treadmill exercise. We measure the energy expenditure for different intensity of exercise and time to use automatic gas analyzer (Respina 1H 26, U.S.). The experiment is approved by Yonsei University IRB (Institutional Review Board) with approval number (1040917-201411HRBR-249-02).

B. Results

1) EPOC is necessary element for estimating total energy expenditure: Figure 2 shows the energy expenditure ratio during and after exercises from 32 different subjects performing high intensity exercise. The x axis represents 32 subjects (1-20 for male, 21-32 for female) and average. The y axis

TABLE I
33 SUBJECTS PARTICIPATED IN THE EXPERIMENT

Characteristic	Mean $\pm$ Std	Range
Age (*year*)	28 $\pm$ 5.31	19 $-$ 41
Weight (*kg*)	68.19 $\pm$ 9.38	49.1 $-$ 92.4
Height (*cm*)	170.61 $\pm$ 6.14	159.6 $-$ 182.8
BMI (kg/m^2)	23.37 $\pm$ 2.29	19 $-$ 28.8

TABLE II
EXPERIMETAL SCENARIOS

Scenario	Content
Prior experiment	• Physical examination • VO_2 max test • Measurement of resting metabolic rate
Scenario 1	• 20 mins high-intensity aerobic exercise • 3 hours rest (lying)
Scenario 2	• 20 mins low-intensity aerobic exercise • 3 hours rest (lying)

represents EE ratio. Exercise EE (EE during exercise) contains averaged energy expenditure ratio for 20-min workout. Total EE contains not only the energy expenditure during exercise (Exercise EE) but also the energy expenditure after exercise (EPOC), i.e., EE for the 3-hour rest period. Interestingly, the EPOC takes up a considerable amount of energy, 57.37 kcal on average, which corresponds to 38.78 % of the Exercise EE (147.95 kcal). Furthermore, EPOC of a certain subject takes up 95.52 % of the Exercise EE in our study (subject 15). For the subject 15, standard deviation of heart rate for 20-min exercise is very high. EPOC must be considered on the EE estimate because the amount of EPOC can never be ignored for every subject who performed in our study.

2) The EE estimates represent very close approximation: Figure 3 plots that the total EE estimation with machine learning-based approaches can achieve very close to actual EE. The x axis shows 6 machine learning models that we have studied with Weka toolkit. The Weka toolkit provides a comprehensive collection of machine learning algorithms and we select the most popular 6 algorithms among them. The y

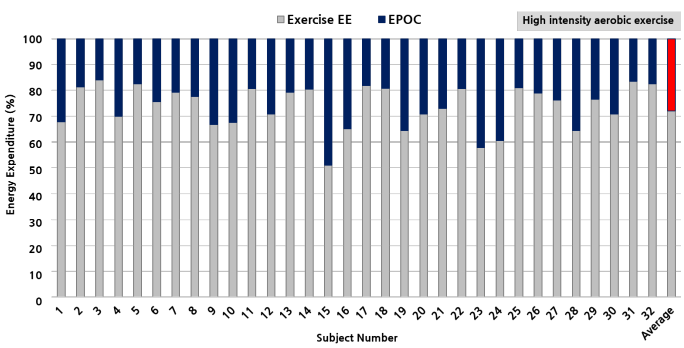

Fig. 2. EPOC is essential element for EE estimation because it takes up 38.78 % of the Exercise EE on average.

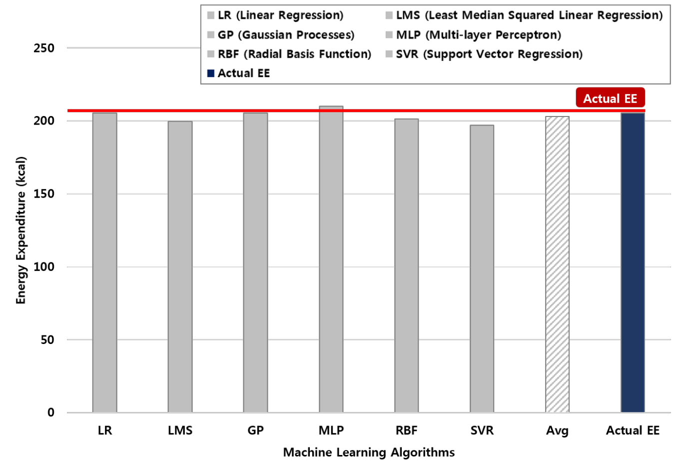

Fig. 3. Our machine learning-based approaches can achieve less than 9 kcal (5 %) error to actual EE.

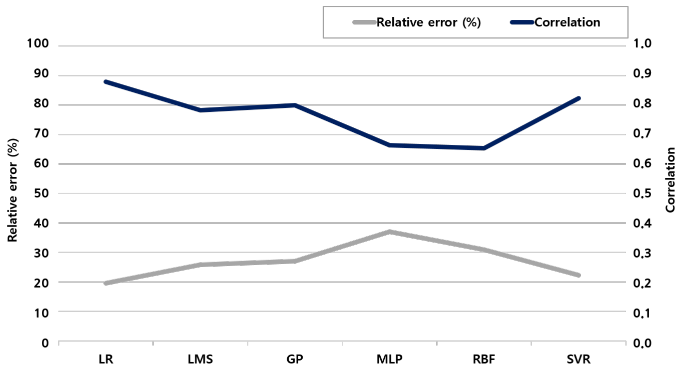

Fig. 4. Linear regression estimation model shows the best result according to the relative error and correlation.

axis shows EE during and after exercise in kcal. We apply the 6 machine learning algorithms to our testing data from 33 subjects in order to generate different regression models for EE estimation. Recently, several machine learning algorithms such as an artificial neural network, a support vector regression, a multiple linear regression, Gaussian processes, and a model tree have been applied for EE estimates [3]. We choose the algorithms which are popularly applied for regression such as a linear regression (LR), a least median squared linear regression (LMS), Gaussian processes (GP), a multi-layer perceptron (MLP), i.e., an artificial neural network, a radial basis function network (RBF), and a support vector regression (SVR). The approaches which have least difference with actual EE in the figure are linear regression and Gaussian processes (each EE difference is just less than 0.02 kcal). Furthermore, we need more detailed analysis for errors of EE estimates to obtain the comprehensive implications.

Figure 4 shows the relative error and correlation with 6 machine learning algorithms. The x axis shows the 6 algorithms. The y axis shows relative error in % and correlation. LR model shows the best result at lowest relative error and

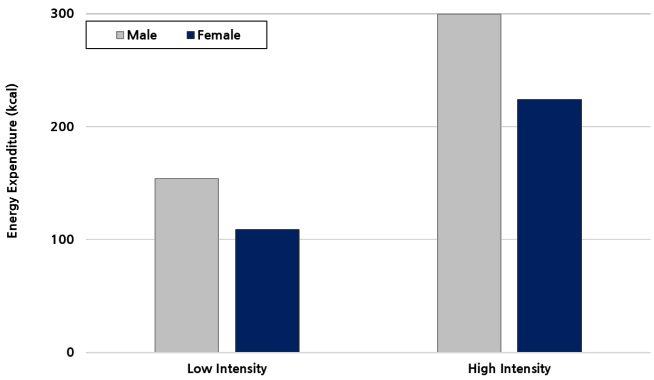

Fig. 5. Energy expenditure increases at high intensity and male.

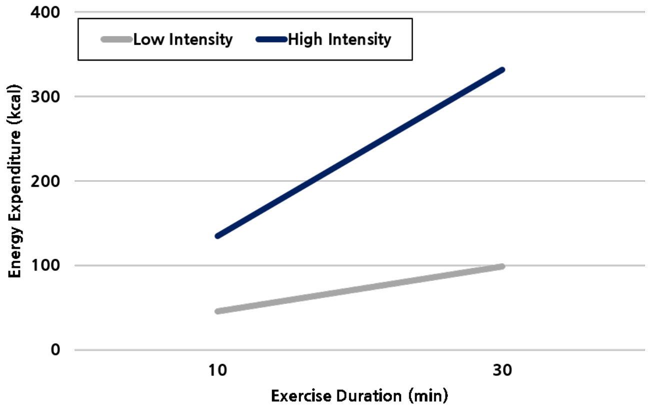

Fig. 6. Energy expenditure increases according to the duration of exercise.

highest correlation. The next is a SVR model. That is why a SVR model depends only on a subset of the training data. Therefore, the relative error and correlation need to be more considered than averaged EE estimation.

TABLE III
THE ERROR AND CORRELATION OF THE PREDICTED EE

Algorithm	Predicted EE (kcal)	RMSE (%)	Relative Error (kcal/min)	Correlation
LR	205.31	0.23	19.61	0.88
LMS	199.67	0.30	25.74	0.78
GP	205.30	0.28	26.92	0.80
MLP	210.19	0.38	36.96	0.66
RBF	201.50	0.35	30.82	0.65
SVR	196.99	0.28	22.22	0.82
Actual EE	205.32			

In order to compare in detail among estimation models, RMSE is a frequently used measure of the differences between values predicted by a model and the values actually observed. Table III shows detailed figures at different kinds of models with the RMSEs, relative errors, and correlation analyses. As shown in Table III, predicted EE of our selected models returns a small difference with actual EE. Estimation results should be individually analyzed with RMSE, relative error, and correlation because the difference value between predicted and actual EE considers averaged EE. A linear regression model (LR), Gaussian processes model (GP), and a support vector regression (SVR) are the reasonable results when considering the RMSE and correlation.

3) Energy expenditure changes according to the duration, intensity of exercise, and gender: On the other hand, energy expenditures are showed differently for intensity of exercise and gender. Figure 5 shows 200-min averaged EE of 33 subjects for intensity of exercise and gender. The x axis categorizes exercise as the intensity. Each intensity is classified by the gender. The y axis shows the total energy expenditure (exercise EE and EPOC) in kcal. High intensity workout consumes more energy than the low intensity on equal terms (difference is 145.53 kcal for male, 115.37 kcal for female). Similarly, male consumes about 1.4 times more energy than female. Intensity and gender are distinguishable elements for estimate EE. The intensity and gender features have a positive effect on accurate estimation model.

Additional result shows how the energy expenditures change with the exercise duration. Figure 6 plots the energy expenditure of a certain subject according to exercise duration. A subject performs 20-min aerobic exercises and 3-hour rests over three nights. The x axis shows exercise duration in minute. The y axis means the EE in kcal. The energy expenditure consistently increases with exercise duration. Interestingly, there is a little increase between 10 and 30 minute in low intensity. In low intensity, EE is gradually increasing compared with high intensity exercise. Therefore, the EE and the exercise duration have a relation of each other.

TABLE IV
THE CORRELATION AND RMSE OF THE PREDICTED EE FOR INCLUDING AND EXCLUDING THE INDIVIDUAL CHARACTERISTICS (GENDER, AGE, HEIGHT, WEIGHT, AND BMI)

Algorithm	Correlation	Correlation (excl.)	RMSE (kcal/min)	RMSE (excl.) (kcal/min)
LR	0.88	0.71	0.23	0.32
GP	0.80	0.72	0.28	0.32
SVR	0.82	0.73	0.28	0.30

4) The individual characteristics are essential value for estimating EE: To evaluate the need of individual characteristics for estimating EE, we apply a machine learning with and without individual characteristics. Heart rate features and time are applied for machine learning. Table IV represents the results which are categorized according inclusion of individual characteristics. *excl.* means the model excluding individual characteristics. Three algorithms with high correlation are selected by our 6 algorithm results. All models including individual characteristics obtain high correlation and low RMSE in comparison with the models excluding the individual characteristics.

5) Our approach can be applied to the off-the-shelf wearable device: Figure 7 represents the application used our EE estimation method which is applied to commercial device.

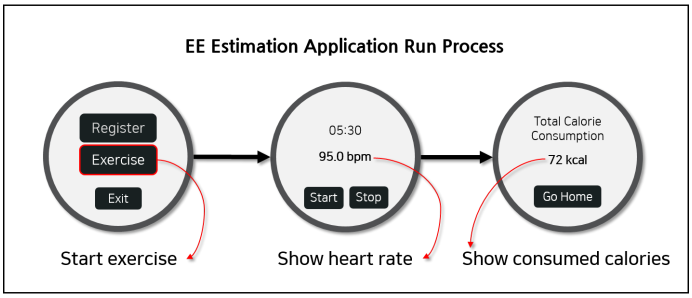

Fig. 7. Energy expenditure estimation Android application runs on the wearable device.

We exploit the LG Watch R as a smartwatch. EE estimation model used machine learning is implemented by using android programming on smartwatch. In future we will evaluate the results between gold-standard value and our estimation model value.

V. Conclusion

In this paper, we present EE estimation models and evaluate our estimation approaches using the heart rate sensor in aerobic exercises, especially presenting the usefulness of EPOC value and individual characteristics for EE estimation. Our 33 subjects perform three types of aerobic exercise including a prior experiment. We observe a significant necessity in adding the EPOC value which takes up 38.78 % of the Exercise EE (EE during exercise).

The estimation results are very satisfactory for everyday use. The results show that the linear regression model (LR) and a support vector regression (SVR) provides the best estimation of EE in RMSE (LR=0.23 kcal/min, SVR=0.28 kcal/min).

There are also a few limitations. First, our method is developed using data from a limited number of exercise in controlled experiment. Motivated by our good results, we plan to carry out experiments for more extensive exercises, e.g., anaerobic exercises. Furthermore, our model will be validated on smartphones or wearable devices. EE estimation value could be presented in real time on the devices.

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