Estimating Heart Rate Variation during Walking with Smartphone

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ABSTRACT

Aiming to realize the application which supports users to enjoy walking with an appropriate physical load, we propose a method to estimate physical load and its variation during walking only with available functions of a smartphone. Since physical load has a linear relationship with heart rate, our purpose is to estimate heart rate with a smartphone. To this end, we build heart rate prediction models which predict heart rate variation from walking data including acceleration and walking speed by machine learning. In order to track unexpected change of physical load, we focus attention on oxygen uptake which has a similar property to heart rate and devise a novel technique to estimate the oxygen uptake from acceleration and GPS data so that it is used as an input of the model. Moreover, to adapt to difference of heart rate variation among individuals, we devise techniques to optimize parameters for each profile-based category of users and to normalize heart rate to absorb individual difference. We applied the proposed method to actual walking data on various routes by different persons and confirmed that the method estimates heart rate variation with the mean error of less than 7 beat per minute.

Author Keywords

heart rate estimation, smartphone sensing, machine learning, walking support

ACM Classification Keywords

C.5.3 Microcomputers: Portable devices (e.g., laptops, personal digital assistants).

INTRODUCTION

Walking is not only effective to reducing body fat and improving muscle strength, but also it is simple and convenient for everyone to try without special equipments. However, walking with high physical load gives non-negligible load on heart and joint, resulting in decreasing motivation for walking, and even hazardous for elderly people or patients of particular diseases. Conversely, walking with low load may result in no effect [11]. Therefore, for sustainable and effective walking, every person must be able to control physical load during walking within an adequate level depending on his/her physical condition. Although the physical load can indirectly be obtained by a heart rate monitor, the cost of purchasing a costly or cumbersome device may spoil simplicity and convenience of walking. So, it is desirable to obtain the physical load by a commodity device used in our daily lives such as a smartphone.

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There are several smartphone applications that can measure heart rate without extra devices. Code4food [6] developed Heart Rate Monitor which measures the pulse by placing a finger on the camera lens. Azumio's Cardio Buddy [8] predicts heart rate from the facial expressions measured by the camera. These applications estimate heart rate with only a smartphone, but they require accurate capturing of finger or face images, thus it is difficult to be used while walking.

As context estimation methods during exercises with a smartphone, physical activity recognition techniques [10, 21] and walking distance estimation technique [5] are proposed. However, to the best of our knowledge, there is little work on estimating physical load during exercises with a smartphone. Some methods (e.g., [23]) have been proposed to estimate exercise intensity in real time, but they do not consider the difference of physical conditions among individuals. In addition, they require users to equip with a heart rate monitor. There is a method that estimates heart rate with accelerometer [25], but this method targets daily living situations (where heart rate is rather stable) and does not take individual difference into account, too.

In this paper, aiming to realize the walking support system which does not deteriorate the advantages of walking (i.e., simplicity and convenience) and adapts to individual difference of physical condition, we propose a method to estimate physical load and its variation of arbitrary person walking along arbitrary route.

To estimate physical load of each individual with a smartphone, we have the following challenges. First, the smartphone cannot directly measure heart rate which is closely related to physical load. Second, heart rate unexpectedly changes depending on exercise intensity. Third, heart rate variation differs among individuals depending on physical condition of each individual. For the first challenge, we construct heart rate prediction models by applying machine learning to the walking data measured by a smartphone and the heart rate data measured by a heart rate monitor. For the second challenge, we focus attention on *oxygen uptake* which has a property similar to heart rate variation, and use it as an input of the model. Since oxygen uptake cannot directly be measured by the smartphone, we devise a novel technique to estimate it from the temporal change of walking speed and walking route's gradient. For the third challenge, we introduce the heart rate normalization technique and optimize some parameters used in oxygen uptake estimation for each category of pre-classified profile-based user categories.

We conducted experiments for 18 subjects and 5 different walking routes and confirmed that our method predicted heart rate with the mean error of less than 7 beat per minute. We also confirmed that the proposed oxygen uptake estimation improved the mean error by more than 10 beat per minute.

WALKING SUPPORT SYSTEM

In this section, first we show the fact that the physical load is inferable by the heart rate. Then, we clarify requirements and show our basic ideas for predicting heart rate variation with a smartphone. We also describe our proposed system which supports users by showing heart rate prediction results during walking.

Index of physical load

Since physical load during exercise is closely related to exercise intensity, RPE (Rate of Perceived Exertion) [4] or heart rate is used as an index of measurement.

RPE is used for measuring the subjective physical load of each individual and known as "Borg scale" defined as 15 levels of subjective physical load, shown in Table. 1. There is a linear correlation between RPE and heart rate (in normal range except for high-intensity part), where each RPE level corresponds to one-tenth of heart rate [3]. This scale is effective to quantitatively evaluate the subjective physical load, but it requires questionnaire or other means to know the physical load of users. Therefore, RPE is not suitable when frequent assessment of physical load is needed.

Table 1. Borg scale

Rating	RPE	Rating	RPE
20		12	
19	Very, very hard	11	Fairly light
18		10	
17	Very hard	9	Very light
16		8	
15	Hard	7	Very, very light
14		6	
13	Somewhat hard		

Due to the above problems of RPE, heart rate is often used as an index of physical load recently. In our proposed method, we also adopt heart rate as the index of physical load.

Requirements and basic ideas

As we described in the previous section, the walking support system should not spoil simplicity and convenience of walking and should allow the user to keep appropriate physical load during walking. Thus, it is desirable that the system can estimate heart rate and its temporal change during walking without costly or cumbersome devices.

In general, the heart rate varies as exercise intensity changes (i.e., changes of walking speed or walking route's gradient). Although walking speed is changed by the user's intention, it looks for the system that the change occurs unexpectedly. In order to allow the user to walk with the appropriate physical load, the system is required to quickly follow and flexibly respond to those changes.

In addition, there are individual differences in the heart rate change depending on age, exercise habits, and so on. Therefore, the system should be able to estimate how the physical load (i.e., the heart rate) of each user changes depending on the user's physical condition.

As a result, we can summarize the system requirements as follows:

1. measure the physical load by commodity devices
2. estimate the temporal change of physical load during walking
3. adapt to individual difference depending on the user's profile

To satisfy the requirement 1, we use the smartphone as a commodity device, and estimate physical load with only functions available on the smartphone, aiming to reduce the cost of purchasing a costly device and the labor for equipping the device. However, the smartphone cannot directly measure physical load or the heart rate. Thereby, we devise a new method that estimates the heart rate by constructing a model which learns association of the walking data such as acceleration, walking speed, gradient and location measured by the smartphone with the heart rate measured by a heart rate monitor.

To satisfy the requirement 2, we utilize the fact that the physical load during walking changes depending on the variation of exercise intensity, which can be calculated by the walking speed and the gradient of the walking route [15]. However, we see that heart rate does not instantly change like exercise intensity, but it gradually changes and converges toward a certain value. Accordingly, it is difficult to exactly associate exercise intensity with heart rate by only detecting the change of walking speed and gradient of the route.

We solve this problem by focusing on *oxygen uptake* which has a feature similar to heart rate. We use it as an input of our heart rate prediction model. However, since the smartphone cannot also directly measure the oxygen uptake, we develop a novel technique to estimate it, which we describe in the next section.

To satisfy the requirement 3, we need to consider the individual difference in the cardiopulmonary function capacity and the heart rate at rest which are dependent on existence of sport habit, age, gender, etc. The trend of heart rate change or the magnitude of the heart rate differs by them.

In Fig. 1, we show the heart rate change when two subjects with different exercise habits walked together on a street at similar walking speed. The heart rate of the subject A who

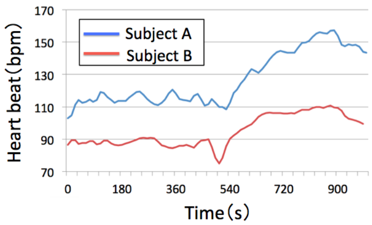


Figure 1. Heart rate change when 2 subjects with different sport habit simultaneously walk on a route at similar walking speed. (subject A without sport habit, subject B with sport habit)

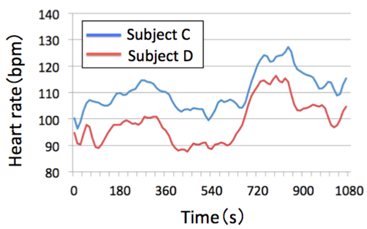


Figure 2. Heart rate change when 2 subjects with different heart rate at rest simultaneously walk on a route. (Heart rate at rest: 68 bpm for subject C, 77 bpm for subject D)

has no exercise habit got higher and increased more rapidly than subject B who has exercise habit. We show another case in Fig. 2 where the trend of heart rate change is almost similar but the magnitude of the heart rate differs between two subjects. We regard that these individual differences are caused by the difference of the heart rate at rest.

There are some existing methods that build the heart rate estimation model for each of users [16]. However, those methods require to collect the walking data of all users in advance, and cannot estimate the physical load for a new user whose data is not available yet. In our proposed system, we create several categories based on user profiles. Assuming that the heart rate of users in the same category changes similarly, we try to adapt the system to the individual difference in the heart rate change by optimizing some parameters used in oxygen uptake estimation for each category. In addition, we remove the difference of the magnitude of heart rate by normalizing heart rate data so that the model learns only the changing patterns of heart rate.

System design

The proposed system targets users who want to take exercise through walking, and is implemented as an application for smartphones with a triaxial acceleration sensor and GPS.

Fig. 3 shows an outline of the proposed system. The system consists of a shared database and a server on cloud and a smartphone carried by users. The shared database accumulates walking data measured by acceleration and GPS sensors of a smartphone. Here, the walking data consists of acceleration amplitude, walking speed, walking route's gradient, oxygen uptake and location on walking routes. The shared database also accumulates physical load and heart rate estimated by the system. The walking data in the shared database are categorized to groups based on user profiles.

As shown in Fig. 3, while the user is walking, the system runs as follows. We adopt half-overlapped time window of length W for uploading the walking data and predicting the heart rate. The value of W is appropriately decided taking into account the sensing frequency of used sensors (e.g., 24 seconds).

First, at the current time t, the user's smartphone extracts the walking data of the current time window $[t - W, t]$ and uploads the data to the server. Then, the server predicts the heart rate at time t and sends the predicted result to the smartphone. Based on the result, the smartphone application urges the user to speed-up or speed-down to keep appropriate physical load, or just shows the predicted result.

The above process is periodically carried out every $W/2$ units of time (at $t + W/2, t + W, t + 3W/2, t + 2W, \ldots$).

PREDICTING HEART RATE VARIATION WITH SMARTPHONE

In order to predict heart rate variation during walking, we construct the heart rate prediction model which associates walking data with heart rate. We utilize a neural network to construct the model, since there is a nonlinear relationship between changes of walking data (acceleration amplitude, walking speed, etc.) and heart rate. The non-linear correspondence of walking data (an input of the model) to heart rate is learned and formed on a neural network.

To capture the effect of exercise intensity and its duration to heart rate change, our method utilizes oxygen uptake as an input to the estimation model, since it has a similar feature to heart rate change.

We build heart rate prediction models in three phases: walking data measurement, feature extraction and model construction.

Walking data measurement

As we described previously, heart rate changes depending on the change of walking speed and route's gradient. In the preliminary experiment for measuring acceleration data while walking on treadmill, we confirmed that walking at different speeds and/or with different gradients leads to different acceleration amplitude. In addition, heart rate is closely related to oxygen uptake since the heart rate during exercise increases or decreases to supply necessary oxygen amounts over the body depending on the exercise intensity change. Considering these observations, we use: (i)–(iv) acceleration amplitude (X-, Y- and Z-axes and composite of all axes); (v) walking speed; (vi) gradient; and (vii) oxygen uptake to predict heart rate because of their big impact to heart rate variation.

Feature extraction

Below, we present methods to extract the features (i)–(vii) described in the previous subsection.

Acceleration amplitude

We measure acceleration data during walking with a 3-axes acceleration sensor and extract acceleration amplitude for each of X-, Y- and Z-axes and for their composite as follows.

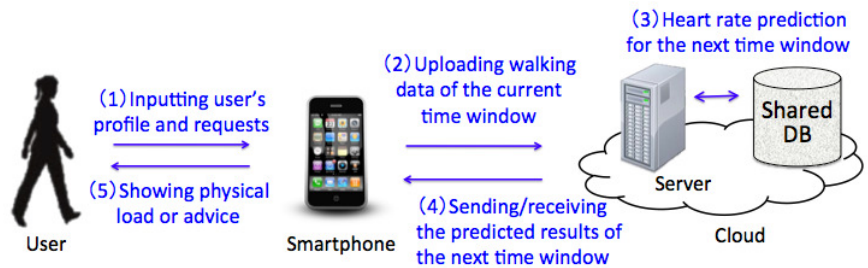


Figure 3. Outline of the proposed walking support system

First, DC components (i.e., direct current with frequency 0Hz produced as a result of applying the acceleration data to the Fast Fourier Transform) are removed in the acceleration data, and all the measured data are divided into fixed size half overlapped time windows. Second, for each window, we calculate the average amplitude.

We extract other features in a similar way from half overlapped time windows of the same window size W.

Walking speed

In principle, we derive walking speed by dividing walking distance by walking duration. However, since locations measured by GPS and the distance calculated by those locations contain non-negligible errors. So, we determined to use dead reckoning [14] which estimates the relative location from a reference point by using inertial sensors such as accelerometers and gyro sensor. We calculate walking speed as follows.

$$S_k = D_k/W \quad (1)$$
$$D_k = ST_k \times SL \quad (2)$$
$$SL = D_{total}/ST_{total} \quad (3)$$

where, S_k[m/sec], D_k[m] and ST_k[step] represent walking speed, walking distance and step count in k-th time window, respectively. In addition, stride length SL[m/ step] is calculated by the total walking distance D_{total}[m] and the total step count ST_{total}. We utilize existing techniques [18, 26] for estimating step count.

Gradient

We calculate the gradient on the target walking route by the following equation.

$$G_k = 100 \times (AD_k/D_k) \quad (4)$$

where, G_k[%], D_k[m] and AD_k[m] represent the gradient, walking distance, and difference of elevation in the k-th time window, respectively. Here, AD_k[m] is calculated as the difference between the 1st location and the last location among all the locations sensed by GPS in each time window.

Oxygen uptake

In this subsection, we describe the detail of our novel technique to estimate the oxygen uptake.

As shown in Fig. 4, when an exercise is taken, oxygen uptake does not instantaneously change to the value corresponding to the exercise intensity, but it approaches to a steady state within 2 to 3 minutes after the start of the exercise. The value corresponding to the exercise intensity is called *oxygen demand*.

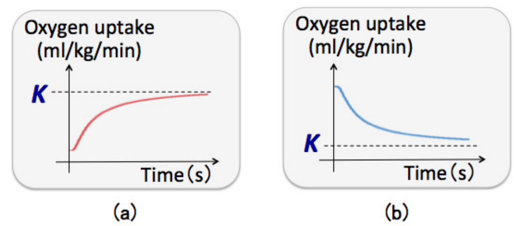


Figure 4. Oxygen uptake change. (a) shows an increasing situation, and (b) shows a decreasing situation, where K represents the oxygen demand.

When taking an exercise with a fixed intensity, the increment of oxygen uptake denoted by U[ml/kg/min] and the decrement of oxygen uptake denoted by D[ml/kg/min] are calculated by the following equations [2].

$$\Delta U = Ke^{-\frac{\tau}{t}} \quad (5)$$
$$\Delta D = K(1 - e^{-\frac{\tau}{t}}) \quad (6)$$

where K[ml/kg/min] and t[s] represent oxygen demand (i.e., oxygen amounts required for the exercise) and the elapsed time, respectively. Moreover, τ represents a parameter representing the time to converge to the oxygen demand.

Assuming that oxygen demand exactly matches the theoretical value of oxygen uptake with a certain exercise intensity, the oxygen demand K[ml/kg/min] can be calculated as follows.

$$K = R + H + V \quad (7)$$
$$R = 3.5 \quad (8)$$
$$H = 0.1 \times speed \quad (9)$$
$$V = 1.8 \times speed \times gradient \quad (10)$$

where R, H and V represent oxygen uptake at rest, oxygen uptake by horizontal component of walking speed, and oxygen uptake by vertical component of walking speed (i.e., difference of elevation), respectively, and $speed$[m/min] and $gradient$[%] represent walking speed and gradient on the target walking route, respectively.

As shown above, variation of oxygen uptake can be calculated, if oxygen demand and exercise duration are known. However, it is a problem that walking speed and gradient during walking vary unexpectedly. Therefore, we calculate the variation of oxygen uptake according to the variation of oxygen demand periodically with a fixed time interval.

Let P denote the time interval for oxygen uptake calculation, and K_i and V_i denote oxygen demand and oxygen uptake at time $t_i (i = 0, 1, 2, 3 \cdots)$, respectively. We calculate V_i by three steps: (Step1) calculating oxygen demand, (Step2) determining the trend of oxygen demand variation, and (Step3) calculating oxygen uptake variation.

In Step1, oxygen demand K_i is calculated by formula (7) during interval $[t_i, t_{i+1}]$. In Step2, we compare K_i with oxygen uptake V_{i-1} at the previous interval $[t_{i-1}, t_i]$, and determine the trend of variation: *increase*, *decrease* or *no_change*. In Step3, oxygen uptake V_i is calculated according to the determined trend. In the case of *no_change*, we regard that exercise intensity did not change, and oxygen uptake variation follows the previous trend.

Below, we show the equations to calculate oxygen uptake increase ΔU and decrease ΔD and to update oxygen uptake V_i.

- When $K_i > V_i$ (*increase*)

$$\begin{aligned} \Delta U_i &= K_i e^{-\frac{\tau}{P}} \\ V_i &= V_{i-1} + \Delta \end{aligned}$$

- When $K_i < V_i$(*decrease*)

$$\begin{aligned} \Delta D_i &= K_i(1 - e^{-\frac{\tau}{P}}) \\ V_i &= V_{i-1} - \Delta D_i \end{aligned}$$

- When $K_i = V_i$(*no_change*)
  - * When the previous interval's trend is *increase*

$$\begin{aligned} \Delta U_i &= K_i(e^{-\frac{\tau}{2P}} - e^{-\frac{\tau}{P}}) \\ V_i &= V_{i-1} + \Delta U_i \end{aligned}$$

  - * When the previous interval's trend is *decrease*

$$\begin{aligned} \Delta D_i &= K_i\{(1 - e^{-\frac{\tau}{2P}}) - (1 - e^{-\frac{\tau}{P}})\} \\ V_i &= V_{i-1} - \Delta D_i \end{aligned}$$

We update the oxygen uptake during walking by repeatedly calculating the above equations over time.

Model construction by machine learning

By using the input parameters derived in previous subsections, we construct the heart rate prediction model.

We use the data mining tool WEKA [24] to build the model. In this tool, the multilayered neural network that has an input layer, a middle layer, and an output layer is available as shown in Fig. 5.

We apply supervised learning as the learning method. Thereby, we let the model learn the relationship between given inputs and outputs using the training data on the neural network. We give the walking data (referred to *test data*, hereafter) measured in the time interval between a certain time t_i and $t_i + W$ (where W shows the window size) including acceleration data and gradient to the model and obtain the heart rate at the time $t_i + W$ as an output.

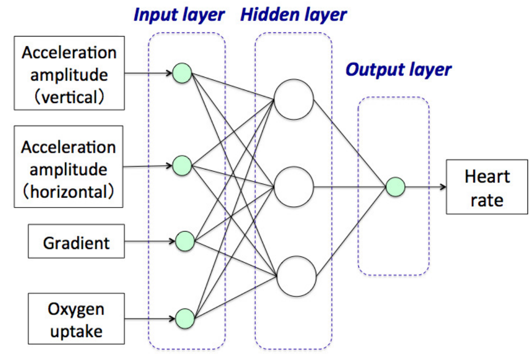


Figure 5. The structure of neural network

As we described in the previous section, prediction of heart rate using the neural network is carried out every $W/2$ units of time. In our experiment, the time to obtain heart rate was less than one second on MacBookAir (Core2Duo 1.86GHz, 2GB memory) when W is 24 seconds. Thus, the heart rate prediction shown on the smartphone is delayed by several seconds including the delay of cellular communication. Since the heart rate gradually changes, we believe this delay is not a big problem for walking support.

ADAPTING TO INDIVIDUAL DIFFERENCE

The method proposed in the previous section does not solve the following problems: (i) the individual difference of heart rate change is not reflected to oxygen uptake calculation; and (ii) this difference cannot be learned by simply building the physical load model from walking data of multiple users.

We assume that the heart rate of users who have similar profiles similarly changes. Then, to solve (i), we introduce some new parameters and optimize those parameters for each user category. In order to solve (ii), we remove the difference of the magnitude of heart rate by normalizing heart rate data so that the model learns only the changing patterns of heart rate.

Introduction of new parameters

Some parameters affect oxygen uptake calculation. Among them, τ affects the convergence speed of heart rate variation and K affects the intensity of exercise. Assuming that the heart rate convergence speed and the intensity of exercise differ among individuals, we introduce new parameters called *characteristic parameters* τ_u, τ_d, M_s and M_g. The parameters τ_u and τ_d represent the reaction rate at the increasing and decreasing periods of oxygen uptake. M_s and M_g are coefficients to reflect the individual difference in oxygen uptake calculation by walking speed and by gradient, respectively. The formulas (9) and (10) are multiplied by M_g and by M_s, respectively, when calculating oxygen uptake.

We show how these parameters improve the accuracy of heart rate estimation.

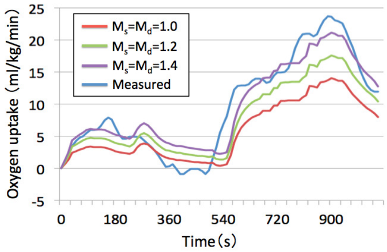


Figure 6. The result of oxygen uptake estimation for different values of characteristic parameters, $M_s, M_g \tau_u = 40, \tau_d = 90$).

Fig. 6 shows the oxygen uptake for different values of M_s and M_g. The figure suggests that by increasing the values of these parameters, the oxygen uptake amount becomes larger. The case of $M_s = M_g = 1.4$ most exactly traces the actual measurement of oxygen uptake values (blue line) in the increase periods.

The values of these characteristic parameters are determined so as to minimize the average errors between the estimated oxygen uptake and the actual one.

Heart rate normalization

As we previously showed in Fig. 2, even if the heart rate of two persons similarly change, the magnitude of the rate might be greatly different from each other. Thus, we normalize the heart rate data for learning.

We denote the heart rate data before the normalization by $Hb_i(i = 1, 2, 3 \cdots)$, the heart rate after the normalization by $Ha_i(i = 1, 2, 3, , ,)$, and the initial heart rate by HR_{start}. Then, we can derive the normalized heart rate by the following equation.

$$Ha_i = Hb_i - HR_{start} \tag{11}$$

When we build a model by the normalized heart rate data, the heart rate predicted by the model reflects only the heart rate change pattern. Therefore, we convert the predicted heart rate to the heart rate with an appropriate magnitude by using the initial heart rate.

Let denote the estimated heart rate before correction by $Pb_i(i = 1, 2, 3 \cdots)$ and the estimated heart rate after correction by $Pa_i(i = 1, 2, 3, , ,)$. Then, we can derive the corrected heart rate by the following equation.

$$Pa_i = Pb_i + (HR_{start} - Pb_1) \tag{12}$$

Here, we assume that the initial heart rate can be obtained as the heart rate at rest.

EVALUATION

In this section, we evaluate the heart rate prediction accuracy of the methods proposed in the previous sections.

Experimental settings

Experimental environment

We used a wristwatch type wireless heart rate monitor, SUUNTO t6d [22] and a smartphone, Sony Ericsson Xperia active [19] for the experiments. Every subject mounted the monitor and the smartphone on the body so that the acceleration direction of horizontal and vertical axes follows Fig. 7. Sampling period was empirically set to 20 milli seconds for the acceleration, 2 seconds for heart rate and 3 seconds for GPS. We set the window size W to 24 seconds based on the sampling periods of the sensors used. We asked 18 subjects (referred to by s1, ..., and s18) consisting of 15 male and 3 female students of our laboratory who are all 20's.

To collect data, we asked each of the subjects to walk on five different routes: A, B, C, D, and E. Fig. 8 shows gradient of each route where horizontal and vertical axes show distance and the altitude, respectively. The distances of routes A, B, C, D, and E are 1,000m, 1,700m, 1,000m, 1,000m, and 1,100m, respectively. We extracted accurate altitudes at each point of the routes from the map published by local government.

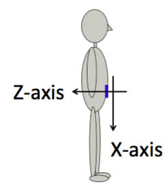


Figure 7. The smartphone is mounted around the waist of each subject so that the acceleration directions, x-, y-, and z-axes follow the figure.

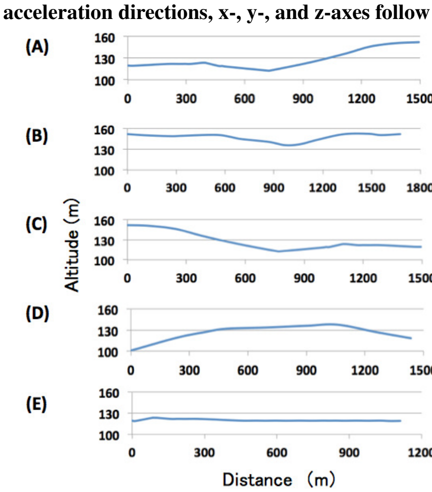


Figure 8. Gradients of five walking routes used for experiments. Vertical and horizontal axes show the altitude and the distance from the starting point, respectively.

Inputs of a heart rate prediction model

Through preliminary experiments, we determined to use the following four input parameters, oxygen uptake (VO), gradient (G), and X- and Y-axes of acceleration (AX and AY) for training heart rate estimation models. Here, VO is calculated with the parameters M_s, M_g, τ_u, τ_d optimized by the user categorization technique proposed in the previous section.

Categorization

This time, we focused only on existence of sport habit and defined the following three categories.

- Category1: users who have taken 30 minutes or more exercise at least twice a week for more than one year

- Category2: users who are neither in category1 nor category3
- Category3: users who have taken almost no exercise (recently and in the past)

Through questionnaire, 5, 11, and 2 subjects were categorized into category1, category2, and category3, respectively.

Models

We trained heart rate estimation models using the above four input parameters (VO, G, AX, and AY) and the normalized measured heart rate at each time window extracted from the walking data of 90 pairs of subjects and routes.

To evaluate the performance of our method depending on the availability of specific subject's or route's walking data, we defined four different types of models: RS00, RS01, RS10, and RS11. Let s and r denote a subject and a route, respectively. We trained a model for each (s, r) pair for every type. The first digit in each model type shows whether the route r's data is used for training the model, and the second digit shows whether the subject s's data is used for training the model.

RS00 is the set of models where each model for testing (s, r) is trained without any data of s and r. RS01 is the set of models where each model for testing (s, r) pair is trained without r's data but with s's data of routes except r. RS10 is the set of models where each model for testing (s, r) is trained without s's data but with r's data of subjects except s. RS11 is the set of models where each model for testing (s, r) is trained with all data except (s, r) data.

Performance metric

We define the accuracy of heart rate estimated by a model as MAE (Mean Absolute Error) between the actual heart rate and the estimated one.

When we use the heart rate estimation model type m and use the heart rate data measured while subject s walks route r as the test data, MAE is defined by the following formula.

$$MAE(s, r, m) = \frac{\sum_{i=0}^{n-1} |phr_m(\frac{W}{2}i) - rhr(\frac{W}{2}i)|}{n} \quad (13)$$

$$n = \frac{2Q}{W} \quad (14)$$

Here, Q and W denote the walking duration and the window size, respectively. $phr_m(t)$ and $rhr(t)$ denote the predicted and real heart rate at time t, respectively.

We also define MAE of each model type m averaged over all subject-route pairs by the following formula.

$$MAE(m) = \frac{\sum_{r \in Route} \sum_{s \in Subject} MAE(s, r, m)}{|Subject| \times |Route|} \quad (15)$$

Here, $Subject = \{s1, ..., s18\}$ and $Route = \{A, ..., E\}$.

Estimation results

Difference among models

First, we show the overall performance of the proposed method in terms of MAE achieved by different model types. We show the result in Table 2.

Table 2. MAE of heart rate estimation by different models

Model	$RS00$	$RS01$	$RS10$	$RS11$
MAE [bpm]	6.78	6.68	6.49	6.41
Standard Deviation	3.45	3.36	3.22	3.56
95% Confidence Interval	6.78 ±0.72	6.68 ±0.70	6.49 ±0.67	6.41 ± 0.75

As seen from the table, all the model types achieved less than 7 bpm MAE. It is known that the heart rate varies even during rest situation. With preliminary experiments, we confirmed that the heart rate variation during rest situation is about 7 bpm on average. In addition, the difference in adjacent levels in Borg scale shown in Table 1 is 10 bpm. From these facts, we can say that the prediction results shown in Table 2 are fairly accurate and practicable.

As expected, the model type RS11 (both the same subject and the same route walking data as the test subject-route pair are available) achieved the smallest MAE and the type RS00 (neither the same subject nor the same route data are available) resulted in the largest MAE. However, the difference is only 0.37 bpm. As a result, we can say that our method can estimate the heart rate variation in reasonably good accuracy even for a new user and for a new route whose walking data are not available. As seen in the table, the result of RS10 is better than that of RS01. This suggests that our methods more accurately predict heart rate of a new user than a new route, although the difference is small (0.19 bpm).

Table 3. Prediction results (MAE) for all subjects/routes (RS00)

Subject	Cat.	A	B	C	D	E	ave.
s1	1	7.61	7.82	4.97	11.32	1.69	6.68
s2	1	16.69	4.62	5.96	15.55	2.98	9.16
s3	1	6.81	10.57	5.38	10.16	8.78	8.34
s4	1	9.03	5.80	7.00	3.97	1.61	5.48
s5	1	3.82	5.25	7.17	4.59	3.91	4.95
s6	2	4.89	2.40	3.08	10.19	3.45	4.80
s7	2	7.59	9.36	3.67	5.15	7.90	6.73
s8	2	9.93	4.89	4.97	11.88	4.36	7.21
s9	2	4.55	3.16	4.66	4.41	5.25	4.41
s10	2	3.48	8.01	7.16	6.61	8.81	6.81
s11	2	8.05	10.73	2.47	11.07	8.13	8.09
s12	2	15.30	7.47	7.19	9.48	6.56	9.20
s13	2	4.70	3.47	4.12	5.50	6.45	4.85
s14	2	5.54	3.12	4.32	17.22	1.12	6.26
s15	2	6.34	6.09	9.68	12.78	13.66	9.71
s16	2	9.79	6.91	8.02	14.19	4.77	8.74
s17	3	5.81	7.09	6.14	4.08	3.41	5.31
s18	3	6.31	9.59	3.94	4.71	1.59	5.23
ave.	-	7.57	6.46	5.55	9.05	5.25	6.78

Difference among subjects and routes

The MAE for all subject-route pairs by model type RS00 are shown in Table 3. As seen in the table, MAE varied among the routes (even with the same subject) and among the subjects (even with the same route).

As an example of accurate prediction of heart rate change, we show the result of Subject10 walking route A in Fig. 9.

The figure shows that our proposed method could almost accurately track the heart rate change.

The mean errors for Subject2, Subject12, and Subject15 are a bit larger than the others as seen from Table 3. One of the primary factors to increase errors is that the inclination of the heart rate variation may not be exactly learned. As seen from Fig. 10 that shows the heart rate change of Subject2 walking route A, the big error was produced between the measured and the predicted heart rate when the rate is high. This is because some error may be introduced in the estimation of walking speed and walking distance due to GPS error and inaccurate information of altitude, resulting in the error of oxygen uptake estimation. Moreover, some subjects may have quite different physical characteristics from other subjects in the same category.

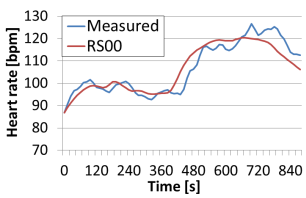


Figure 9. Prediction of heart rate change (s10, A)

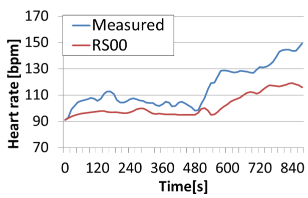
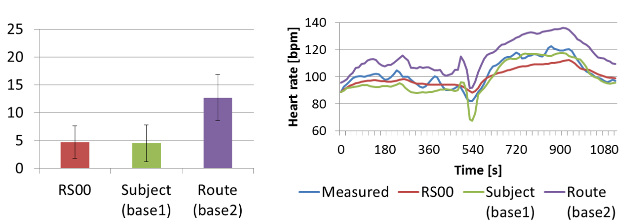


Figure 10. Prediction of heart rate change (s2, A)

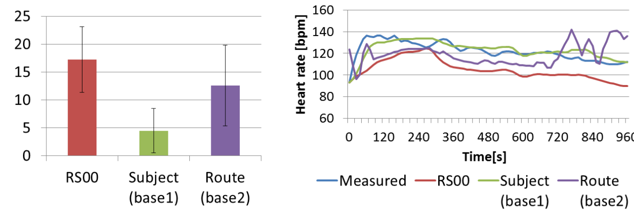
Comparison to baselines
To show the effectiveness of the proposed method, we defined two baselines: (baseline 1) training a model with a single subject's data of four routes and testing the subject's data of one remaining route; and (baseline 2) training a model with a single route's data of 17 subjects and testing the route's data of one remaining subject. To calculate baselines, we picked up two pairs: (s13, A) and (s14, D) which achieved small and large MAE, respectively, by model RS00 (see Table 3). For these pairs, we compared the baseline results to the result obtained by model RS00. We show the comparison results in Fig. 11 and Fig. 12.

Fig. 11 (a), which corresponds to the good accuracy case, suggests that baseline 1 (with the model trained by the same subject data) achieves the smallest MAE, but the difference between RS00 and baseline 1 is small (0.17bpm), that means our proposed method (RS00) achieves reasonably good accuracy in estimating heart rate variation. MAE of baseline 2 (with the model trained by the same route data) is larger than RS00. This is because the difference of heart rate variation among subjects is big as shown in Fig. 11 (b).



(a) Mean absolute error (b) Heart rate variation

Figure 11. Comparison with baselines in small MAE case (s13, A)



(a) Mean absolute error (b) Heart rate variation

Figure 12. Comparison with baselines in large MAE case (s14, D)

Fig. 12 (a), which corresponds to the bad accuracy case, suggests that baseline 1 achieves the smallest MAE, and RS00 results in the largest MAE. The difference between RS00 and baseline 1 is rather large (12.7bpm). The difference between RS00 and baseline 2 is relatively small (4.6bpm), but the variance of RS00 is smaller than that of baseline 2. As seen from Fig. 12 (b), heart rate variation trends of RS00 and baseline 1 are similar and RS00 better tracks heart rate variation than baseline 2. However, there are big constant distance between two curves. This may be caused by the ineffectiveness of the proposed categorization and normalization techniques. We need to devise a better mechanism for adapting to the individual difference.

As a result, we can say that our method (RS00) achieves good accuracy comparable to baseline 1 and baseline 2 for most of the subject-route pairs (e.g., MAE less than 10 bpm in Table 3), but we also confirmed that in some of the subject-route pairs, the proposed method (RS00) results in fairly bigger MAE than the baselines (especially baseline 1) due to insufficient adaptation to individual difference.

Effectiveness of oxygen uptake
We have evaluated effectiveness of introducing oxygen uptake (VO) by comparing the MAE obtained from models trained by two different sets of input parameters: with VO (VO, G, AX, AY, and heart rate) and without VO (G, AX, AY, and heart rate). Here, we used the model type RS11.

We show the error between the actual heart rate and the predicted one in Fig. 13.

The MAE without VO and with VO are 16.71 bpm and 6.41 bpm, respectively, and the variance with VO is much smaller than that without VO. This result clearly shows the effectiveness of the proposed oxygen uptake prediction.

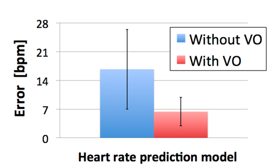


Figure 13. Effectiveness of oxygen uptake

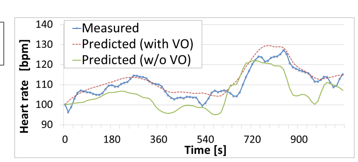


Figure 14. Heart rate change over time

We also show part of the heart rate prediction result over time in Fig. 14. Although the case without VO (green line) reflects change of the actual heart rate to some extent, the case with VO (red line) more accurately predicts the rate change especially in the beginning phase of walking. This is because the oxygen uptake is calculated by temporal change of exercise intensity and thereby it could reflect the quick transition from the rest situation to the exercise situation.

Effectiveness of normalization

To evaluate effectiveness of the heart rate normalization technique, we compared the prediction results obtained from the models trained with and without normalization. We used model type RS11.

In Fig. 15, we show the mean absolute error calculated for each case. We see that applying the normalization technique reduced the MAE by about 1.45 bpm, which is rather small. However, the normalization reduced the variance to a great extent.

We show the temporal heart rate change in the case that normalization effect is prominent in Fig. 16. In this figure, even the prediction without normalization (red line) well follows the change of heart rate, but it predicted the heart rate by about 10 to 20 bpm higher during the whole walking period. On the other hand, we see that the case with normalization (green line) could much more accurately predict heart rate. This shows that the proposed normalization technique can contribute to adapting to the individual difference in heart rate variation and improve the prediction accuracy.

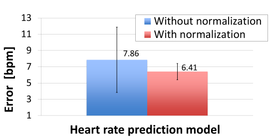


Figure 15. Effectiveness of normalization

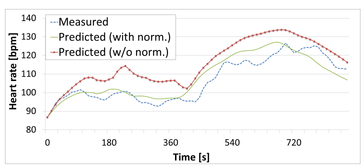


Figure 16. Heart rate variation with/without normalization

RELATED WORK

We briefly survey existing studies related to this work.

Activities recognition during exercise with smartphone

Recently, the smartphone has become a commodity device and it incorporates various sensors and functions such as acceleration, gyro, and GPS sensors. Thereby, many efforts have been devoted to detecting human's physical activities during exercise with smartphone.

Khan et al. [10] and Sun et al. [21] proposed methods to recognize daily physical activities by using a triaxial acceleration sensor of a smartphone. They classified some activities with different exercise intensity (e.g., walking, running, down-stair, up-stair, etc.), and achieved the recognition accuracy of about 94%.

There are many other studies utilizing the smartphone to recognize physical activities such as estimating the step count during walking [12, 18], identifying users moving direction [7], and estimating user's location by dead reckoning [5, 9, 20]. These methods can be used with our method to derive accurate walking speed during walking.

Accelerometer reorientation and gradient estimation

Mohan et al. [13] proposed a method that automatically adjusts the directions of 3 axes of the 3-axis accelerometer of the disoriented smartphone so that X-axis directs to the front, Y-axis to the right, and Z-axis to the ground. This method can match the disoriented directions to well-oriented directions by measuring Euler angles.

Bae et al. [1] proposed a road grade estimation method based on the angles of GPS antennas fixed on the roof of a car. This method needs the high-precision GPS equipment and needs to fix them on the roof of a car. Shalholm et al. [17] proposed a road grade estimation method that uses the low cost GPS equipment without fixing on the roof and without extra sensors. Unfortunately, these methods are developed basically for vehicles, and cannot be directly applied to walking support.

The above methods can enhance practicality of our method when integrated.

Heart rate prediction

As an approach without the heart rate monitor, Xiao et al. [25] proposed the heart rate prediction model using a neural network. They used acceleration data of each axis measured by a triaxial acceleration sensor and the heart rate predicted in the previous time step as inputs and achieved the mean absolute error of about 5 bpm. This result suggests that a neural network is useful for associating exercise intensity with heart rate. However, the proposed model is not appropriate for our purpose, because it targets daily living activities in which heart rate variation is much smaller than physical activities like walking. Also, this study estimates heart rate of a time window t_i from acceleration data measured and the heart rate estimated in the previous time window t_{i-1}. That means the estimation error will be accumulated over time. Especially when the heart rate quickly varies like during walking, we thought that this method would not be suitable. This study does not take into account the individual difference of heart rate, too.

Exercise intensity estimation

Tapia et al. [23] proposed a method that recognizes physical activities such as sitting, walking, running, and cycling and estimate their exercise intensity with an acceleration sensor and a heart rate monitor. This method is costly for users to equip with a heart rate monitor, as mentioned before. Moreover, they classify the exercise intensity of physical activities into some types (e.g., 2 mph with 0% grade) defined by the authors, so they cannot estimate quantitative exercise intensity. It does not take into account individual difference, too.

CONCLUSIONS

In this paper, we proposed a method which estimates the physical load and its minute change during walking only with available functions of a smartphone. Our evaluation experiments showed that the proposed oxygen uptake estimation technique is effective for accurate heart rate estimation considering individual difference. In addition, by determining some characteristic parameters for each category, our method could estimate the heart rate with the mean error less than 7 bpm for 18 subjects and five different routes.

Our experiments also revealed that our proposed method is not perfect: the estimation accuracy was not very good for some subjects; and the proposed categorization and normalization techniques sometimes did not sufficiently adapt to individual difference. Thus, as future work, we should develop more sophisticated classification of users with more diverse profiles (e.g., considering age, and gender) and improve categorization and normalization techniques. We also need to take into account the fact that users' conditions are not always perfect and the heart rate may be influenced by weather (especially temperature), tiredness due to recent exercise, and so on. We also need to clarify the impact of each of factors that contribute to the estimation error. To make the proposed method more practical, we need to integrate various techniques such as the automatic calibration of acceleration axes (e.g., in [13]) even when the mobile phone is in the user's pocket, and automatic gradient estimation (such as in [1, 17]).

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