Heart Rate Prediction for Easy Walking Route Planning

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Abstract: In this paper, aiming to support easy walking route planning, we propose methods for predicting a heart rate along the arbitrary route without walking data, and recommending a semi-optimal walking route based on the predicted results. In our method, we build a model to predict the heart rate during walking with expected walking speed and gradient along a target route, and compute a semi-optimal walking route (near least physical load route satisfying calorie/distance constraints requested by a user) by using the model. In order to evaluate the accuracy of the prediction model, a walking experiment with 39 participants was conducted. The result showed that our model could predict the heart rate with mean absolute error (MAE) of 6.31 beats per minute on average. We also confirmed that the route recommended by our method satisfied calorie/distance constraints requested by a user while keeping the average and the maximum physical load (in terms of heart rate reserve) at 29.5% (light load) and 44.4% (moderate load), respectively.

Key Words: heart rate prediction, walking route planning, smartphone sensing, machine learning, health support.

1. Introduction

Walking has been gaining much attention for the prevention of chronic diseases such as hypertension and diabetes caused by lack of exercise because walking is not only effective to health enhancement such as body fat reduction and muscles development but also easy and simple for everyone. However, for continuous and effective walking, physical load during walking needs to be appropriately adjusted depending on physical/health conditions of walkers.

Physical load degree can be estimated by a heart rate monitor because it is closely related to the heart rate. Physical load during exercise has a strong relationship with exercise intensity. Therefore, the rate of perceived exertion (RPE) defined by Borg [1] is often used as an index to measure it. Recently, many wearable devices including smart watches have hit the market. With these devices, we can easily measure the heart rate or pulse rate. Although they can measure the current pulse (therefore record the past heart rate data), they cannot predict a future heart rate and thus cannot effectively help walkers appropriately control their physical load. Prediction of a future heart rate during walking is especially important since this makes it possible to plan a walking route that satisfies walkers’ requirements (walking time/distance and calorie expenditure, etc) and keeps their physical load within an appropriate range.

RunKeeper [2] and iSmoothRun [3] are smartphone applications that support walking. These applications show the current heart rate on the smartphone’s screen by connecting the heart rate monitor to the smartphone via Bluetooth. However, since they have no function to predict the future heart rate change, what the walker can do when the heart rate becomes too high is to reduce the walking speed only after he/she knows the fact. If prediction of the future heart rate is possible, walkers can adjust the walking speed before the heart rate becomes too high or even plan the appropriate walking route that is not likely to cause a too high heart rate.

In this paper, we propose a method that constructs a model for predicting heart rate change from the gradient of a walking route and expected walking speed so that the heart rate change is estimated before walking. By using the model, we also propose a method for computing a semi-optimal walking route satisfying user request for helping walkers plan an easy and effective route. In our proposed method, an objective function with parameters consisting of user requirements (such as walking time/distance, calorie expenditure) and physical load (heart rate reserve), is defined, and we derive the semi-optimal walking plan (near least load route with walking speed at each interval) by using a heuristic algorithm.

We have conducted evaluation experiments with 39 participants walking three different routes to examine (1) if the derived walking route satisfies user requirements and (2) if the predicted heart rate change is sufficiently close to the actual one. As a result, heart rate prediction within 6.72 beats per minute in mean absolute error was achieved for every combination of the participant and the walking route on average. The average and maximum physical load (in terms of heart rate reserve) while actually walking along the recommended walking plan were 29.5% (light load) and 44.4% (moderate load), respectively.

2. Related Work

There are many walking support applications such as RunKeeper [2] and iSmoothRun [3]. These applications can coach the user by audio guidance. In addition, both a route creation function and a route sharing function are provided on the web. A heart rate is an important factor for effective and safe walking. Therefore, various heart rate monitors that can be connected to various walking support applications via Bluetooth (heart rate profile) are sold in the market. These applications not only record the heart rate but also can instruct the user to decrease the walking pace if the heart rate rises quickly or exceeds a certain limit. However, if the user forgets to wear a
heart rate monitor, the applications cannot instruct the pace control because the user’s heart rate cannot be obtained. Moreover, these applications may keep the physical load within an appropriate range by the pace control function but may violate constraints of walking time and/or calories requested by the user if the walking route is not appropriately selected.

Various methods for predicting a heart rate have already been proposed. For example, some methods [4],[5] predict a heart rate after a certain period of time with a heart rate monitor. In these methods, a heart rate variation associated with a walking speed is predicted by the model that correlates a heart rate to music tempo. The heart rate measured by a heart rate monitor and a walking speed is used as inputs to the model. Since these methods assume to use a heart rate monitor, they are not suitable for our purpose. In addition, since these methods assume that the user can change a walking speed according to the instruction, the timing of change and the variation amount of the speed are known. Furthermore, experiments and evaluation are conducted on a treadmill, which is an easier environment for predicting the heart rate.

A route planning system recommends some candidate routes based on various conditions. The most common condition is the efficiency. In this case, the most efficient route will be recommended based on the efficiency such as travel time, costs and distances [6],[7]. On the other hand, there are many route recommendation methods based on another criterion other than efficiency [8]–[13]. P-Tour [8] recommends an optimal tour for visiting various sightseeing spots efficiently under some conditions such as a time constraint and preference level for each spot. Happyroute [9] recommends a comfortable route in an urban area. Similarly to these methods, our proposed method computes a walking route along which the heart rate (or physical load) is kept low enough while satisfying the user’s requirements.

In our previous work [14], we developed a method for estimating the current heart rate during walking by using only a smartphone. This method creates a model for estimating the heart rate from a walking data by using machine learning. This method relies on the following theories: the amplitude of the acceleration is affected by walking speed; the degree of walking load is changed by a variation of exercise intensity; particularly, (T1) the exercise intensity is strongly affected by walking speed and the gradient of the road [15]; and (T2) the heart rate changes to supply demanded oxygen over the user’s body, and thus the correlation between the oxygen uptake and the heart rate is high [16]. Based on these theories T1 and T2, this method used the following features for predicting the heart rate: (i) The amplitude of the acceleration (X, Y, Z, resultant), (ii) the walking speed, (iii) the gradient of the road, and (iv) the oxygen uptake. Although the heart rate has strong correlation to these features, the relationship between variation of a heart rate and variation of each feature is non-linear [17]. Therefore, a neural network is employed as a learning algorithm suitable for learning the non-linear relation. To construct a model, it classifies users into three categories based on the existence of exercise habits in the past and the duration of exercise habits. As a result, this method succeeded to estimate a heart rate by using only a smartphone without wearing any other sensors. However, this method requires the current walking data as input and still cannot predict a future heart rate variation.

In this paper, to predict a future heart rate before walking, we construct a novel heart rate prediction model by extending our prior work [14] mentioned above.

3. Walking Planning System Based on HR Prediction

3.1 Overview

The purpose of the proposed easy walking planning system is to reduce the risk of possible injury and/or a too high physical load caused by an inappropriate walking plan. For this purpose, the proposed system aims to compute the easiest walking route that may not cause a high physical load during walking.

A heart rate is needed to know the physical load. Therefore, we set the following as the requirements of the proposed system.

Requirement 1: The system can predict heart rate change before walking.

Requirement 2: The system can compute as easy walking route as possible.

Figure 1 shows the overview of the proposed system satisfying the above requirements.

The proposed system predicts a heart rate only with sensors equipped with a smartphone, aiming to realize a highly usable system.

The input of the system is (i) user profile (gender, age, height, weight, exercise habit, etc.) and (ii) user request (start/return points/areas, walking distance/time and calorie expenditure). The system computes walking plans satisfying the constraints given by (ii) and computes a quasi-easiest walking route. We predict the physical load from the heart rate since they are closely related to each other. We extend our previous method [14] to predict heart rate change without actual walking.

3.2 Relationship between Heart Rate and Physical Load

A walker’s physical load is derived by using heart rate reserve and the classification table shown in Table 1.

Heart rate reserve (called HRR, hereafter) shows the exercise intensity assuming that the heart rate at rest state is 0 % and the maximum heart rate (defined as 220 minus age) is 100 %, and is calculated by Karvonen’s formula [18] described as Eq. (1).

In Eq. (1), $HR_{rest}$, $HR_{rest}$, and AGE denote the measured heart rate, the heart rate at rest, and the user’s age, respectively, and HRR is defined as

$$HRR = \frac{HR_{rest} - HR_{rest}}{220 - AGE - HR_{rest}} \times 100.$$

(1)
Table 1 Classification table of physical load (for exercises within 60 minutes).

| Physical Load | Heart Rate Reserve (%) |
|---------------|------------------------|
| Very light    | < 20                   |
| Light         | 20 – 39                |
| Moderate      | 40 – 59                |
| Hard          | 60 – 84                |
| Very hard     | ≥ 85                   |
| Maximal       | 100                    |

*1 the maximum heart rate is the average value when healthy adults do maximum physical load exercises.

Table 2 Relationship between road gradient and walking speed.

| Gradient Gi (%) | Walking speed (m/min) |
|-----------------|-----------------------|
| 4 ≤ Gi < 8      | 70                    |
| 0 ≤ Gi < 4      | 80                    |
| -4 ≤ Gi < 0     | 90                    |
| -8 ≤ Gi < -4    | 100                   |

3.3 The Proposed Method for Predicting Heart Rate without Walking Data

Our previous method [14] uses (i) acceleration data (X, Y, Z axes and mixed), (ii) walking speed (calculated by (i)), (iii) road gradient, and (iv) oxygen uptake (calculated from (ii) and (iii)) for heart rate estimation. For the prediction of a future heart rate, walking data used for the prediction should be available in advance. Therefore, acceleration data used in our previous method cannot be used for prediction of the heart rate. Therefore, we propose a method using walking data available in advance: (1) walking speed, (2) road gradient, and (3) oxygen uptake, for prediction of heart rate. Below we will describe how these features can be obtained.

**Walking speed**

Walking speed is used as a parameter in which any value can be set. In general, a human’s walking speed naturally varies depending on the gradient of the road. For example, when walking up a hill, the walking speed will decrease. Taking this into account, we empirically set the walking speed depending on the road gradient as shown in Table 2. When predicting the heart rate on a walking route, the walking speed is selected depending on the gradient of each interval/segment of the road. Hereafter, a walking route with recommended walking speed at each interval is called the walking plan.

**Road gradient**

Road gradient is calculated from the geo-points and the map data by using the following formula. We suppose that the altitude information for any geo-point is available through on-line data by using the following formula. We suppose that the altitude information for any geo-point is available through on-line data by using the following formula. We suppose that the altitude information for any geo-point is available through on-line data by using the following formula. We suppose that the altitude information for any geo-point is available through on-line data by using the following formula. We suppose that the altitude information for any geo-point is available through on-line data by using the following formula. We suppose that the altitude information for any geo-point is available through on-line data by using the following formula.

\[
G_i = \frac{AD_i}{Dist_i} \times 100. \tag{2}
\]

**Oxygen uptake and its difference among individuals**

The method to compute the oxygen uptake is proposed in our previous method [14]. In this method, oxygen demand is periodically calculated from the average walking speed and the average road gradient in the current period. The oxygen uptake is also periodically updated based on the difference of the oxygen demand from the immediately preceding period. In this paper, we use the oxygen uptake computed based on this method.

The oxygen uptake is computed by periodically increasing it \((+AD)\) or decreasing it \((-AD)\). The increased or decreased amount depends on the change of the exercise intensity. The exercise intensity can be calculated from the walking speed and the road gradient [15]. Thus, we just explain how to calculate oxygen uptake. Specifically, letting \(V_i\) and \(K_i\) denote the oxygen uptake and the exercise intensity at \(i\)-th time interval (whose length is \(P\)), respectively, \(V_i\) is calculated by the following formula:

\[
V_i = V_{i-1} + K_i e^{-\frac{T_i}{\tau_u}} \text{ if } K_i > K_{i-1}, \tag{3}
\]

\[
V_i = V_{i-1} - K_i (1 - e^{-\frac{T_i}{\tau_d}}) \text{ if } K_i < K_{i-1}. \tag{4}
\]

Here, if \(K_i = K_{i-1}\), then the previous increasing/decreasing trend is continued.

**Individual difference in oxygen uptake**

In Eqs. (3) and (4), \(\tau_u\) and \(\tau_d\) denote the parameters representing the speed of oxygen uptake change as time progresses, respectively. Note that parameters \(\tau_u\) and \(\tau_d\) are different among persons. Thereby, we use a heuristic method to derive values of these parameters for each user category so that the HR prediction errors are minimized.

One may think that oxygen uptake is not needed as a feature since it is calculated from walking speed and road gradient that can be used as features. However, the ordinary neural network does not well learn oxygen uptake from walking speed and road gradient, and our previous experiments showed that the mean absolute error (MAE) of heart rate estimation without oxygen uptake is 16.71 beats per minute, which is much worse than the case with oxygen uptake whose MAE is 6.41 beats per minute [14]. Therefore, we will use oxygen uptake as a feature also in our method in this paper.

The above features are used to predict the heart rate. Since the relationship between the features and the heart rate is nonlinear, we use a neural network which can effectively learn the nonlinear relationship.

We use an ordinary neural network with a hierarchical structure consisting of input, intermediate, and output layers. Here, walking speed, road gradient and oxygen uptake are the input to the neural network and the heart rate is the output.

3.4 Walking Plan Recommendation based on Physical Load

We show the detail of our proposed method which computes and recommends the semi-optimal walking plan from the user profile, start/return points/areas, walking time/distance, and calorie expenditure requirements.

Candidates of walking plans are narrowed based on the conditions input as user requirements. As the conditions, the start point \(p_s\), the and goal point \(p_g\), the maximum walking distance \(D\) and time \(T\), and the desirable calorie expenditure \(Cal\) are given as mandatory input parameters.

The parameters \(D\), \(T\) and \(Cal\) must be input in this order. When \(D(m)\) is determined, the possible range of \(T(min)\) is determined to \([\frac{D(m)}{100(m/min)}, \frac{D(m)}{90(m/min)}]\) by using Table 2. Then, \(Cal(kcal)\) is also determined by formula (5) from the range of \(T\), Table 3 and user’s weight \(Weight(kg)\).

The proposed algorithm selects a semi-optimal walking plan from all candidates satisfying these conditions by the following steps.
Table 3 Relationship between walking speed and exercise intensity.

| METs | Walking speed (m/min) |
|------|-----------------------|
| 3.1  | 70                    |
| 3.3  | 80                    |
| 3.6  | 90                    |
| 4.0  | 100                   |

1. We define a search area $SA$ as a circle centered at the start/return point with a diameter equal to $D$. If the return point is different from the start point, $SA$ is defined as a circle centered at the middle point between $p_i$ and $p_k$ with a diameter equal to $D$. Let $P$ denote the set of intersections included in $SA$.

2. An intersection $p \in P$ closest to $p_j$ is selected. Pre-determined number of possible routes starting from $p_j$ to reach $p_k$ within $SA$ are generated at random; then the set of routes $R$ satisfying the conditions on $D$, $T$, and $Cal$ are extracted. Each route $r \in R$ is evaluated by the objective function which will be defined by (6).

3. The route with the highest evaluation value is selected and shown to the user.

The distance of a walking route is calculated using a map data. We suppose that a map data is given as a directed graph. Let $\text{dist}(p, p')$ denote the function to calculate the shortest distance between two intersections $p$ and $p'$. Move time between intersections is calculated from distance and speed. Let $\text{speed}(p, p')$ denote the user’s walking speed between intersections (points) $p$ and $p'$. When a user moves from $p$ to $p'$, moving time $t(p, p')$ can be calculated by $t(p, p') = \text{dist}(p, p') / \text{speed}(p, p')$.

We denote a candidate route $r$ by $r = (p_1, ..., p_k)$. Here, $r_i$ denotes the $i$-th intersection visited in $r$.

Let $\text{Bur}(p)$ denote the physical load at intersection $p$. Calorie expenditure $Cal$ is calculated by the formula (5) according to the guideline issued by Ministry of Health, Labour and Welfare [19].

$$Cal = METs \times \text{Weight} \times T \times 1.05$$

Here, 1.05 is a well-used co-efficient to calculate the calorie expenditure. $METs$ is an index of the intensity of exercise and/or living activities and shows magnification of calories consumed for exercise/activity compared to the rest state. Table 3 shows the value of $METs$ depending on the walking speed.

3.5 Objective Function

When evaluating each walking plan, various criteria exists. In this paper, our proposal is to find a walking route that minimizes a walker’s physical load while satisfying the user request. For this purpose, just summing up the physical load at each interval is not good because the walking plan with extremely slow walking speed or the plan with small total physical load but very high load at some intervals might be recommended. Therefore, we define the objective function to be minimized by the following formula (6):

$$f(r) = \alpha \frac{\sum_{i=1}^{k} \text{Load}(p_i)}{k}$$

$$+ (1 - \alpha) \frac{\sum_{i=1}^{k-1} \text{speed}(p_i, p_{i+1})/S_{\text{max}}}{k}.$$  \hspace{1cm} (6)

Here, $\alpha$ ($0 \leq \alpha \leq 1$) is a coefficient to the average physical load (the first term) and the average walking speed (the second term) at all intervals in the walking route. The value of $\alpha$ value can be empirically determined (0.6 was used for experiments in Section 4).

The function $\text{load}(p_i)$ denotes the normalized physical load (the value between 0 and 1) at the point $p_i$ and $S_{\text{max}}$ denotes the maximum walking speed, respectively. The objective function is defined so that slower average walking speed deteriorates the evaluation value. Moreover, the larger $\alpha$ allows the higher average walking speed.

4. Evaluation

In this section, the accuracy of heart rate prediction and the effectiveness of the route recommendation are evaluated through experiments.

4.1 Evaluation of Heart Rate Prediction

This subsection describes the evaluation methods and results of the heart rate prediction model.

4.1.1 Evaluation methods of the heart rate prediction model

To evaluate the accuracy of the heart rate prediction model, an experiment was conducted with 39 participants consisting of 10 females and 29 males with different profiles (diverse heights [ranging between 156 cm and 181 cm] and weights and different exercise habits). To obtain walking data, each of them walked three routes (A, B, and C) wearing a heart rate monitor and a smartphone.

Figure 2 shows the mount position of each device. Each participant mounted a heart rate monitor on the chest and a smartphone on the waist. Additionally, the accelerometer of the smartphone was fixed as shown in Fig. 2. The sampling periods of the accelerometer, the heart rate monitor, and the GPS sensor are empirically set to 20 ms, 2 s, and 3 s, respectively.

Figure 3 shows the altitude of each walking route. This altitude data is acquired at 50 m intervals for each route by Altitude application programing interface (API) of GSI. The value of altitude acquired by this API is more accurate than that by Google API because GSI altitude data was acquired by airborne laser surveying. The distances of routes A, B, and C are 1500 m, 1700 m, and 1500 m, respectively.
Taking into consideration the biases of the physical condition and the weather, we asked participants to have enough sleep time on the day before the experiment. The experiments were conducted for two weeks, from 19 to 30, October 2015. The weather and the air temperature on the experiment days were only sunny and between 20°C and 25°C, respectively.

As described in the related work section, the way of heart rate change differs among people. Our previous method [14] created models for three user categories. Here, aiming to realize more accurate classification of users, we define five user categories based on gender and exercise habits of users as follows.

category a: male group with neither present nor past exercise habit
category b: male group with either present or past exercise habit (except for category c)
category c: male group with both present and past exercise habit
category d: female group with no present or past exercise habit
category e: female group with present or past exercise habit

The number of participants in each category was as follows: 6 participants for category a; 18 for category b; 5 for category c; 4 for category d; and 6 for category e.

4.1.2 Accuracy of prediction models

We conducted leave-one-participant-out cross-validation for each pair of category and route; that is, walking data measured by all participants in the category-route-pair except the test participant are used as training data. The evaluation index is the mean absolute error (MAE) between actual data and prediction data of the heart rate. Our purpose is to know physical load level from heart rate reserve (HRR) by using Table 1. As we defined HRR in Eq. (1), the only absolute error (not relative error) from actual heart rate affects the HRR value. That is why we use MAE among many other metrics like the mean relative error (MRE) as an evaluation metric.

The mean absolute error $MAE(u, r)$ for a participant $u \in \{u_1, u_2, ..., u_39\}$ walked on a route $r \in \{A, B, C\}$ is calculated by Eq. (7).

In this equation, $\text{phr}(u, k)$ and $\text{rhr}(u, k)$ are the predicted heart rate and the real (actual) heart rate in the $k$-th period. Each period has a time window of W seconds and the consecutive periods are half-overlapped. The number of periods $n$ is calculated by Eq. (8). In this equation, $T_r$ is the total walking time for a walking route $r$.

$$MAE(u, r) = \frac{\sum_{k=1}^{n} |\text{phr}(k) - \text{rhr}(k)|}{n},$$

$$n = \frac{2T_r}{W} - 1.$$  

In our preliminary experiment, we confirmed that even in the rest state, up to 7 bpm heart rate variation was observed. Thus, we set our target estimation accuracy to be MAE within 7 bpm.

The results of MAE for each category and each route are shown in Table 4. The average MAE for all categories is 6.31 bpm. The average MAEs for each category (right-most column) and for each route (bottom row) are less than 7.00 bpm, respectively. The average MAE for each pair of category and route is less than 8.00 bpm, where MAE of category d is slightly higher than others. These results show that our method almost achieves our target accuracy. The standard deviation for all categories is 2.19 bpm. The standard deviation for category c is the smallest (1.69 bpm), but those for the other categories are more than 2.0 bpm. This result suggests that the user classification method for category c is appropriate, but more detailed classification may be needed for the other categories. Overall, it is shown that our proposed method can predict the heart rate at a certain accuracy for various types of users.

Figure 4 shows the result of the heart rate prediction for a particular pair of a participant (in category c) and a route (route A). The result shows that our proposed method can predict the heart rate in accordance with the change of the actual heart rate caused by road gradients.

4.2 Evaluation of Computed Walking Route

This subsection describes the evaluation methods and results of the route recommendation.

4.2.1 Evaluation methods of route recommendation

In order to evaluate the effectiveness of the route recommendation, a walking experiment for the predicted routes was conducted. The purpose of the experiment is (1) to confirm if the recommended route satisfies the requirements, (2) to compare the predicted heart rate with the actual heart rate while walking, and (3) to assess the quality of the recommended route by comparing with other routes.

The profile and requirements of a participant in this experiment are shown in Tables 5 and 6. The participant is male and belongs to category b. As the requirements, the walking distance $D$ was set to less than 2000 m, the walking time $T$ to less than 25 min, and the expenditure of calories $Cal$ to more than 80 kcal. The start and goal points were set to the same point as shown in Fig. 5. A circle in Fig. 5 is the search area of routes determined based on the specified walking distance.

First, some routes were generated according to the requirements and map conditions. Second, the heart rate on those routes was predicted by using the heart rate prediction model of the corresponding category. Third, the degree of the physical load was calculated from the predicted heart rate using HRR. Finally, the optimal route was selected based on the Eq. (6). Here, we empirically set $\alpha$ to 0.6.
Table 5 User profile.

| parameter     | value |
|---------------|-------|
| sex           | male  |
| age (year)    | 23    |
| height (cm)   | 174   |
| weight (kg)   | 61    |
| heart rate at rest (bpm) | 65 |
| category      | b     |

Table 6 Requirement of route search.

| requirement               | value      |
|---------------------------|------------|
| walking distance \([D]\)  | 2000 (m)   |
| walking time \([T]\)      | 25 (min)   |
| expenditure of calories \([Cal]\) | 80 (kcal) |

Fig. 5 Position of start and goal.

4.2.2 Evaluation results of route recommendation

Figure 6 shows the optimal (route 1) recommended by the proposed method. The points in Fig. 6 are the selected intersections. The recommended route has the distance \(D\) of 1961 m, the time \(T\) of 24 m, and the expenditure of calories \(Cal\) of 82.52 kcal. We see that the route satisfies all the requirements.

Figure 7 shows the results of the predicted and actual heart rate while walking along the recommended route. As seen from Fig. 7, the predicted heart rate is well tracking the actual heart rates. However, in some parts, especially at around 800 m point (a steep hill), the predicted heart rate is not very accurate. This is because we did not have sufficient walking data in steep hills for training. Overall, we believe that our proposed method can be used to predict the heart rate practically enough for route planning purpose.

The average HRR while walking the route based on the predicted heart rate was 29.5%, which means that the physical load is “Light” from Table 1. Also, the maximum HRR was 44.4%, which signifies “Moderate” load. This result shows that our method can recommend a route that can keep the physical load during walking within an appropriate range.

Next, we compare the recommended optimal route (route 1) with another route (route 2), which was not selected but was one of the candidates for recommendation. Figure 8 shows the route 2. The points in Fig. 8 are the selected intersections. The route 2 has the distance \(D\) of 1924 m, the time \(T\) of 24 min and the expenditure of calories \(Cal\) of 80.97 kcal. The route 2 also satisfies all the requirements.

Figure 9 shows the results of the predicted and actual heart rates while walking route 2. As seen from Fig. 9, the predicted heart rate was also near the actual heart rate. The average HRR in the route 2 based on the predicted heart rate was 37.6%, which means “light” physical load from Table 1. Also, the maximum HRR was 52.5%, which corresponds to “moderate” load. However, the physical load of the route 2 is higher than the optimal route (route 1). This shows that the proposed method can find the better route keeping both average
and maximum loads as small as possible.

5. Conclusion
In this study, we built a new model to predict the heart rate based on gradients and walking speeds, and proposed a method to compute a semi-optimal walking route by using the prediction models. In order to evaluate the accuracy of the prediction models, the walking experiments with 39 participants were conducted. The results showed that our model could predict the heart rate with MAE 6.31 bpm on average. Moreover, the walking experiment on the predicted route was conducted, and we confirmed that the computed route satisfied all of the user requirements and kept the physical load in a reasonably low range.

This paper aimed to minimize a walker’s physical load while walking, but setting another objective function is possible and of great interest for future work. For example, for training purposes, keeping a relatively high (but not too high) walking load may be necessary, while for recreation purposes, finding scenic routes satisfying user requests [13] may be required. We will explore the possibility of applying our methods to various different purposes in the future. Moreover, our proposed method relies on oxygen uptake estimation from walking speed and road gradient, but we have still not yet clarified the direct relationship between the walking intensity and the actual oxygen uptake. Such clarification through measurement of the actual oxygen uptake while walking could be a part of our future work.

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