# A Smart Walking Navigation System based on Perceived Exertion

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## ABSTRACT

In recent years, the growing trend of personal well-being has led an increasing number of people to engage in walking related activities to improve their physical health. As such, it is becoming increasingly important to develop walking navigation systems which are able to effectively support such activities. The conventional walking navigation systems found in modern smart phone devices usually recommends the shortest route to a destination and are not aimed at facilitating health promoting walking activities. Therefore, in this paper, we propose a novel walking navigation system which takes into consideration the rate of perceived exertion (based on the walking distance, geographical elevation and heart rate data) and the avoidance of dangerous locations and the possibility of passing through highly rated scenic locations (based on social network data from twitter) when recommending a route. Finally, we describe the results of a feasibility experiment study carried out to test the routes in the system.

### ACM Classification Keywords

H.5.1 Multimedia information Systems: Hypertext navigation and maps

### Author Keywords

Waking Navigation; Walking Support Systems; Geotagged tweet analysis; Danger Avoidance

## INTRODUCTION

The recent growing trend of personal well-being has led an increasing number of people to engage in walking related activities for a variety of health related purposes, such as to reduce weight and maintain their physical fitness. Various government policies and initiatives (such as [9]) have been put in place to help raise awareness about the importance of physical exercise. However, even though people are aware of the importance of physical exercise, it is difficult for them to engage and continue in such activities for a prolonged period of time. As such, there is an emerging need for the development of walking navigation systems which are able to effectively support health promoting walking activities.

Despite walking navigation systems becoming more commonplace in modern smart phone devices, the conventional navigation systems were not created with the goal of facilitating health related walking activities and generally recommends the shortest route to a selected destination. In this paper, we propose a smart walking navigation system which is aimed especially at supporting health related walking activities. To create a walking route which is effective, enjoyable and safe for users, we describe how an appropriate perceived exertion load could be determined based on information such as the walking duration, geographical inclination and heart rate and describe how the system could help users avoid accident prone locations and suggest pleasurable walking routes which passes through scenic locations by using social network data from twitter.

The appropriate perceived exertion load refers to an exertion load which is appropriate for a user based on their physical characteristics and their purpose of exercise. Overall, the walking load of each route is calculated by combining data from the measurement of the level of inclination and distance within the route with heart rate data. To help avoid dangerous routes, data from geo-tagged twitters are also obtained and analyzed. For instances, various phrases which denote a dangerous conditions, such as "it's dangerous", "I'm afraid" or "It's dark" are collected and used to estimate the level of danger on a route.

In addition, to facilitate a more enjoyable walking experience, data which could indicate the presence of appropriate resting locations is also taken into consideration. This includes data which describes locations with good panoramic views or seasonal sightseeing locations (for cherry blossom and autumn leaf viewing etc.). Similar to how we obtained information


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**Figure 1. The concept map of the smart navigation system**

about dangerous routes, the system collects data about appropriate resting locations from geo-tagged tweets. Highly evaluated scenic locations are identified and considered in the route recommendation.

Overall, this paper presents a smart walking navigation system which recommends a route based on the rate of perceived exertion and the possibility of passing through highly rated scenic locations and avoiding dangerous locations. In this paper, we discuss how such a navigation system could be implemented. Afterwards, we describe a feasibility experiment carried out to test the routes in the proposed system.

## RELATED RESEARCH

Route recommendation systems have been developed and used for a variety of purposes such as in tourism and health care (see [12] [14] [1] etc.). For those aimed at supporting walking related activities, previous research tend to focus on issues related to health and safety (such as providing a walking route which can effectively improve the health of a user during exercise activities) and issues related to improving the underlining walking experience (such as providing a walking route which is aesthetically pleasurable).

Examples of walking support and route recommendation systems which focus on health and safety include one system devised by Takaishi et al [13] which aimed to provide older users with a personalized walking plan by combining data from a GPS and a heart rate monitoring device. This was done to provide better walking instructions for older people looking to go walking as a way to exercise and improve their health. However, the adoption and execution of this "walking plan" is still reliant on the motivation of the users and the system does not automatically change or recommend the route in real time. In terms of safety, Kim et al.[5] proposed a system which helps users avoid dangerous routes by using data from geo-tagged tweets. Another study proposed a route recommendation system which recommends a walking route based on the number of calories which users wish to lose [14]. The overall aim of the system is to provide continuous support for users who wish to take daily walks for exercise, with the system attempting to recommend different routes each day to prevent boredom. To help reduce stress during walking related activities, research carried out by Kitabayashi et al [6] used biological data such as the user's heart rate and data related to the walking environment to analyze and estimate the level of stress. The main aim was to provide a walking path which is physically less stressful, especially for populations such as older people. Overall, even though such systems are helpful in recommending a route which is appropriate as a means of exercise, there is still the problem of motivating users to participate in the walking activity. To better motivate users, we believe that it would also be advantageous to also consider information from the environment within the walking route as well (such as potential scenic locations within the walking route).

Various systems have also been developed to help provide users with a more pleasurable walking experience. For instance, one study proposed a route recommendation system which is not based on the shortest distance, but on the potential enjoyment quality within the route [11]. Abdallah et al [2] in the meanwhile, proposed a route recommendation system for those seeking to explore a city. The aim was to provide users with recommendations of routes which contain interesting elements (scenic views etc.) by analyzing geo-tagged photos from photosharing sites such as Flickr. Other researchers have also proposed a walking support system which allows users to share scenic locations within a walking course with others[8]. Although such systems are helpful in providing a motivating walking route for users, they generally do not include biological data from users in their recommendation and therefore tend not to take into account the physical characteristics of users (such as their physical ability or exertion) which could also significantly influence the walking experience.

## A SMART WALKING NAVIGATION SYSTEM BASED ON THE RATE OF PERCEIVED EXERTION

### Overview

In this paper, we propose a Smart Walking Navigation System which recommends a route based on the user and path characteristics, taking into account the rate of perceived exertion and the possibility of avoiding dangerous locations and the ability to pass through highly rated scenic locations. An overview of the system is shown in Figure 1. Users first start by inputing information about their age, gender, resting heart rate and desired walking duration. Based on this, the system would then determine an appropriate walking distance. Within this walking distance area, the system would obtain data about the inclination level, the heart rate of previous pedestrians, the presence of potentially dangerous locations (such as narrow paths, heavy traffic and train crossings) and locations which are scenic or popular with tourists. Based on this information, several walking routes would then be recommend to the user. In the following section, we provide more details about the data used in the recommendation of the routes and discuss the method which can be used to obtain the data.

## The data

*heart rate data*

To help determine the appropriate exertion load, the user's target heart rate is calculated [4]. The equation used to calculate the target heart rate is as follows:

$$\mathbf{thr_i = (220 - age_i - rhr_i) * tc + rhr_i}$$

In the equation, thr refers to the target heart rate , rhr refers to the resting heart rate and tc refers to the target coefficient.

| Rating | Perceived Exertion | Intensity | Heart rate |
|---|---|---|---|
| 20 | Maximum exertion | 100.0 | 200 |
| 19 | Extremely hard | 92.9 | |
| 18 | | 85.8 | 180 |
| 17 | Very hard | 78.6 | |
| 16 | | 71.5 | 160 |
| 15 | Hard | 64.3 | |
| 14 | | 57.2 | 140 |
| 13 | Somewhat hard | 50.0 | |
| 12 | | 42.9 | 120 |
| 11 | Light | 35.7 | |
| 10 | | 28.6 | 100 |
| 9 | Very light | 21.4 | |
| 8 | | 14.3 | 80 |
| 7 | Extremely light | 7.1 | |
| 6 | No exertion | 0.0 | 60 |

**Table 1. The relationship between the Rate of Perceived Exertion and heart rate as described by the Japanese Institute of Health and Exercise**

Table 1 shows the relationship between the Rate of Perceived Exertion and heart rate. In this study, the intensity level most effective for dieting (which has been defined as between "Light" and "Hard") which is used as the target coefficient in the equation has been set to around 40 to 60 percent.

*The level of inclination*

Geospatial elevation data from the the Geospatial Information Authority of Japan was used to calculate the level of inclination for a specific location [3]. The inclination data was acquired by using elevation data from a 5 meter grid interval. The open source software QGIS [10] was used to create a road network containing the latitude, longitude and elevation information.

*Information about scenic locations, word of mouth reviews and dangerous locations*

Information about scenic locations in the area could be obtained from geo-tagged tweets combined with data from sightseeing guide websites. For instance, tweets with phrases such as "the cherry blossoms are beautiful" and "The night view is pretty" could provide information about possible scenic locations in the area. A key advantage of using geo-tagged tweets is that it allows us to obtain information about not only the popular tourist-based scenic locations in the area, but also allows us to identify less well known ones as well. In addition, using geo-tagged tweets allow the system to obtain scenic location information which is more context specific and up-to date (such as flower viewing spots which only appear during certain seasons or night viewing spots which are most beautiful during night time). Information about potentially dangerous routes is obtained in a similar manner, by identifying words and phrases such as "dangerous" and "scary" from geo-tagged tweets.

## Implementation of the walking route recommendation system

*Estimating the walking speed based on age and gender*

When using the system, the users would input how long they wish to walk (their desired walking duration). To be able to accurately determine the length of the recommended route, it is necessary to estimate the potential walking speed of each user. Information about the age and gender of the users is used to help determine the walking speed. The average walking speed of people when they walk around indeterminately could be found at [16]. Based on this data, the appropriate walking distance (i.e. the desired length of the route) is calculated.

*Obtaining map and elevation data*

The open source software QGIS was used to obtain Open street map (OSM) data [7] as well as data about the elevation, latitude and longtitude.The data obtained in this study is centered around the city of Kyoto, Japan at the latitude-longitude coordinate of 6,662. Every OSM data point was given elevation, longitude and latitude data from QGIS. The length of the road was calculated using differences in longitude/latitude. The inclination between two points was calculated based on the difference in elevation.

*Route recommendation through Dijkstra's algorithm*

Traditional walking navigation systems calculate the shortest route between the starting point and target destination using Dijkstra's algorithm. In this study, in addition to the walking distance, we would also take into account the perceived rate of exertion, the presence of potentially dangerous areas as well as the availability of scenic locations.

Initially, the proposed system randomly selects multiple candidate sites based on the target walking distance. The inclination data and information about possible dangerous and scenic locations are obtained for the points on the shortest route to the candidate sites (calculated using Dijkstra's algorithm). Afterwards, the system recommends routes by considering the perceived exertion load and the possibility of passing through safe and scenic locations.

For example, if a walking distance of 800 meters is required, multiple points from within the edge of the approximately 800 meter circular radius range are selected and the shortest route from the starting spot to these points are calculated using the Dijkstra's algorithm. When the desired walking distance is reached, the points are then made into candidate sites. See Figure 2 for an example of the routes proposed by the system.

After the candidate sites have been obtained, data about the inclination would be acquired for the points on the routes to the candidate sites and used to investigate the physical exertion load based on the targeted heart rate of the user. In the future, the heart rate data would be used to help predict the level of perceived exertion on different routes. Geo-tagged tweets were also obtained for the points on the route. In regards to the tweets, in the current system, the number of tweets were used as an indicator of the popularity of the location, regardless of whether they were positive or negative in nature. In the future, we would look into using sentiment analysis to separate the negative locations from the positive ones. Overall, both data related to the inclination and the tweets would be displayed for the routes to the candidate sites.

To test the feasibility of the currently proposed system, an experiment study was carried out. The main aim was to determine whether the perceived exertion load of the user is influenced by the inclination within the route and whether geo-tagged tweets could be a good indicator of the enjoyment within the route.

## FEASIBILITY STUDY OF THE ROUTE RECOMMENDATION SYSTEM

An experiment study was carried out to test the feasibility of the proposed method. Figure 2, shows an example of 8 different waking navigation routes recommended by the method proposed in the paper. The targeted walking distance (from the start location "S" to the points G1 to G8) is around 800m.

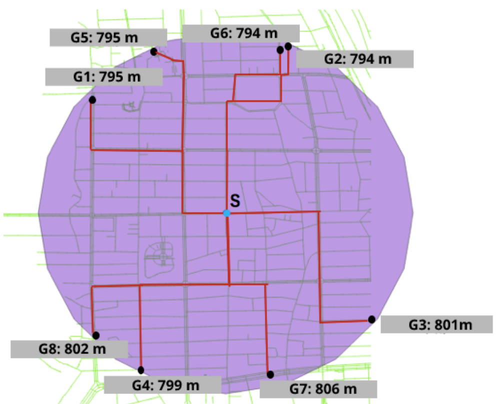


**Figure 2. The 8 example recommended routes**

| Target destination | Total distance | Combined upper elevation | combined lower elevation | Number of tweets |
|---|---|---|---|---|
| G1 | 795m | +13m | -3m | 14 tweets |
| G2 | 794m | +3m | -5m | 9 tweets |
| G3 | 801m | +1m | -11m | 8 tweets |
| G4 | 799m | +9m | -6m | 43 tweets |
| G5 | 795m | +11m | -2m | 12 tweets |
| G6 | 794m | +4m | -3m | 26 tweets |
| G7 | 806m | +1m | -11m | 25 tweets |
| G8 | 802m | +3m | 0m | 30 tweets |

**Table 2. Information about the inclination of the recommended route and the number of tweets**

Table 2 shows the total distance, inclination and total number of tweets from the start location to the target destinations points (G1 to G8).

To test the feasibility of the recommendation method, three participants were asked to walk through the routes recommended by the system. Overall, the routes to the destinations G2 and G4 were selected as they had a large difference in tweet numbers but were similar in terms of changes to the level of inclination. In addition,the routes to the destinations G1 and G3 were also selected as they were similar in terms of tweet numbers but had large difference in inclination change. Participants wore a smart watch which measured their heart rate as they walked through the route. In addition, participants were also asked to rate their experience while walking the route. They were asked to rate three factors 1) how easy they felt the route was 2) how enjoyable was the route and 3) whether they would like to walk on the route again on a 7 point Likert scale.

The results are shown in table 3. As expected, the average heart rate of participants increased substantially for routes with high upper elevation (G1). In addition, participants felt it was easier to walk on routes with a low combined upper elevation (G2 and G3) than those with a high combined upper elevation (G1 and G4). Thus, the results suggest that the level of inclination change within a route could be a good indicator of the perceived exertion of users on that route.

The influence of the number of tweets on user enjoyment and motivation was less clear. There seems to be a trend in that for routes with a high number of tweets, the reported level of enjoyment and motivation seems to be higher than routes with a lower number of tweets (i.e. G1 being higher than G2 and G3 and G4 being higher than G3). Overall, the system could be further refined by using methods such as sentiment analysis to analyze the tweets in more detail, using a method similar to [15] to incorporate the tweets to a route area.

| Route | Ave Heart rate | Ave Rating Ease | Ave Rating Enjoyment | Ave Rating Motivation |
|---|---|---|---|---|
| G1 | **100.0** | 3.3 | **5.7** | **5.7** |
| G2 | 88.3 | **6.0** | 5.0 | 4.3 |
| G3 | 89.0 | 5.7 | 3.0 | 3.7 |
| G4 | 87.7 | 3.7 | 5.0 | 4.3 |

**Table 3. The results of the feasibility experiment study (N=3)**

## SUMMARY

In this paper, we have proposed a smart walking navigation system which recommends a walking route that takes into account the perceived exertion load (based on the walking duration, heart rate and inclination etc.), the possibility of avoiding dangerous locations and the ability to pass through highly rated scenic and popular locations. The overall aim of the system is to provide a walking experience which is enjoyable, safe and beneficial to the physical health of the user. We have described how such a system could be implemented.

In addition, we have provided the results of an experiment study carried out to test the feasibility of the proposed method, showing how the routes suggested by the system could influence the level of perceived exertion for users. In the future, we aim to refine the proposed method by using sentiment analysis to analyze the tweets and determine the scenic and dangerous locations within the route. In addition, we would also examine a more personalized approach towards recommending the appropriate walking distance for each user based on their physical abilities and health conditions (i.e. by using information from smart watches which can collect health related data to infer the physical ability of users etc.).

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