MEDINFO 2017: Precision Healthcare through Informatics
A.V. Gundlapalli et al. (Eds.)

doi:10.3233/978-1-61499-830-3-146

Developing a Mobile Wellness Management System for Healthy Lifestyle by Analyzing Daily Living Activities

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Abstract

It is important to protect health and improve quality of life for people, without causing them inconvenience in today's world. Since most people are living a busy life dealing with various activities at work, school, or home, there is a need for systematic analysis of their life patterns. However, since person's life patterns could change depending on ambient environmental factors, an effective management scheme to specify one's state is required. We propose a method, in this paper, to support and enhance the personal healthy life patterns by analyzing the daily life data that has been continuously recorded by wearable sensors, such as activity trackers. We implement a mobile wellness management system by learning RNN-based user's lifestyle model, and developing behavior recommendation using greedy policy. We also consider user context and feedback to personalize each user's lifestyle.

Keywords:

Health promotion; Life Style: Fitness Tracker

Introduction

Recently, Quality of life (QoL) is an important concept for general public, as well as researchers. Researchers have increasingly conducted research to improve QoL and daily lives of people. The QoL is defined as a subjective assessment of individual's well-being that includes both physical and psychological aspects of daily living [13]. Specifically, in case of patients with chronic diseases, such as diabetes, QoL in the short-term could be poor and may affect the motivation to manage one's own health in the long-term [10, 15]. In such situation, it is required to provide appropriate treatment concerned with not only long-term, but also short-term aspects.

As quality of daily living is related to QoL, it is frequently assessed in various questionnaires of psychometric assessment tools [6, 13]. However, most people have different quality of daily living due to the diversity of their living environment. To analyze and model each individual's lifestyle, we need to monitor entire sequences of activities of the person's daily life over time. Nowadays, there are many wearable sensors to collect behavioral and physiological data from users' daily living activities. Some researches have used these sensors that collect physiological signals, such as blood pressure, heart rate, heart rate variability (HRV), and skin conductance, in order to recognize user's affects [2; 5; 7; 12; 14].

Activity trackers, like pedometer, are useful tools to support tracking movements and manage users' activities by utilizing a cloud service on Web or mobile app. In general, activity trackers are wearable devices, such as wristband or belt, and they send various types of collected data to a smartphone and/or a server [6]. The stored data can be visualized in various ways, such as statistics of movements or graphical charts showing trends, to motivate users to reach their goals.

Today, activity trackers track multiple types of data, including step counts, movement speed, distance, heart rate, and sleep patterns. Sometimes, exercise or dietary habits can also be recorded on a mobile app or Web site that manufacturers support. Fitbit is one of the famous brands in activity tracker available in the market. It offers many kinds of wristband-type devices that can count steps, floors and distance that user has moved, and also measure heart rate and active time.

Other famous products are Jawbone devices. Figure 1 shows one such wristband activity tracker, Jawbone UP3. It has electrodes to sense user's bio signals and a band surface to indicate small icons to display various states, such as active state, sleep mode, or notification arrival. Jawbone device and mobile app work on several smartphone platforms, and provide attractive features to track user's movements, heart rate, sleep patterns, and personal records on diet and activity. It can also indicate detailed information including awake time and the level of sleep (deep or light sleep).

Therefore, we choose the Jawbone's activity trackers for our experiments. Two main reasons of our choice are as follows:

1. They apply three bio-impedance signals, such as heart rate, respiration, and galvanic skin response (GSR), to collect data of user's activities; and
2. They track not only daily activities, but also detailed levels of patterns while the user is sleeping.

In order to utilize more useful services in combination with existing healthcare services, there have been various attempts to model the state of physical information of a particular user along with underlying measured values from various sensors and devices. Pande et al. [9] and Bouarfa et al. [3] conducted a study to model the energy consumption of a person according to the activity, and Cheng et al. [4] performed a study to model changes in heart rate during the course of various activities. Austin et al. [1] and Lipton et al. [8] attempted to accurately model and predict user's heart rate; thereby, identifying medical important situations, such as heart failure.

Figure 1– Jawbone UP3 activity tracker

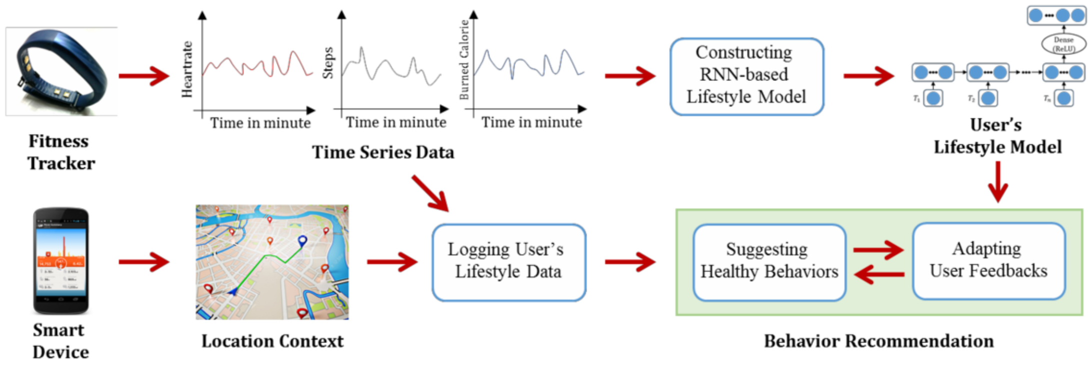


Figure 2 – Conceptual diagram of mobile wellness management system

However, this research has focused on analyzing the user state, on the basis of the present time, based on data already collected from an external device, such as a wristband-type sensor. It is, however, difficult to predict a future activity or change in situation for the user in order to guide a systematic health promotion plan. If user's activity pattern is predicted through user modeling using machine learning technology, such as DNN, it is possible to suggest proper activities at an appropriate time. Also, in order to automatically determine whether the activity is performed without causing inconvenience to the user, it is necessary to be able to observe the change of the user's activity or situation at the relevant time, and obtain feedback on the results of the activity recommendations.

In this paper, we propose a personalized wellness management system based on mobile environment to improve lifestyle quality by analyzing the recorded time series data in daily life. Figure 2 shows overall concept of our proposed system. First, we collect three types of time series data, such as heart rate, step counts, and amount of burned calories. We also log the changes of the user's location context. Based on these collected data items, we analyze and extract user's lifestyle patterns that will be used as input features. To construct an appropriate model to represent the characteristics of user's daily lifestyle, we apply a recurrent neural network (RNN) model. Lastly, we recommend healthy behaviors for the specific user, underlying the lifestyle model built in previous step. For each recommendation, the user can give particular feedback to adapt the RNN model for supporting personalization to the user's lifestyle.

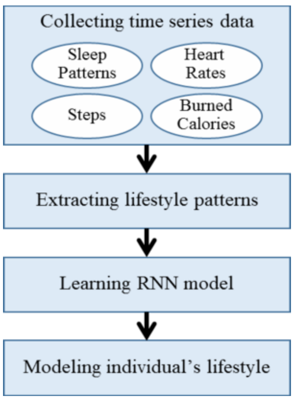


Figure 3– Block diagram for modeling lifestyle patterns of a particular user

Methods

In this section, we explain overall architecture of our mobile wellness management system in detail (Figure 3). First, we describe how our system analyzes user lifestyle, and models an individual's lifestyle patterns based on the time series data that have been obtained by wearable sensors. Second, we explain a process of activity recommendation to enhance user's wellness by utilizing the lifestyle model. Third, we introduce functionality of our mobile system, and illustrate user perspective using Android platform.

Collecting time series data

The wearable device, Jawbone UP3, collects and provides four types of time series data (i.e. sleep pattern, heart rate, step count, and amount of burned calories) from the user who is attached to the device. While only sleep patterns have nominal values over time, such as awake, light, or deep sleep, other three series have numeric values. In the data scheme of UP3, sleep pattern and heart rate are managed by different entities separately; however, both step count and burned calories are stored in a single entity named as 'moves'. These are written in JSON (JavaScript Object Notation) format. Here we show partial examples for each data gathered by UP3.

- Sleep pattern:

– [{"depth":1, "time":1448227726}, {"depth":2, "time":1448228457},
…,
{"depth":2, "time":1448244340}, {"depth":3, "time":1448245505}]

- Heart rate:

– [{"time_updated":1460041251, "resting_heartrate":62, "sleep_ranges":[[1459960311, 1459993298]], "bg_move_day_hr_ticks":[{"hr":67, "time":1459955996}, {"hr":69, "time":1459993357},
…,
{"hr":55, "time":1459993228}], "xid":"piqj71jQzD8o4kfqUacmm1NTWAkPuB x_", "type":"heartrate"}]

- Step count and burned calories:

– [{"time_completed":1445712639, "distance":3, "calories":1.15767812729, "steps":5, "time":1445712576, "speed":0.047619048506,
…,
{"distance":2, "time_completed":1445782637, "calories":1.17605400085, "steps":7, "time":1445782573, "speed":0.03125}]

Extracting lifestyle patterns

The raw data from UP3 should be preprocessed before fitting the RNN model. Due to the difference in data type, we analyze three time series data, i.e., heart rate, step count, and burned calories. The sleep patterns are used for context information. We create three separate vectors for each collected data. The changes of user's location context provide potential clues regarding daily activity and lifestyle pattern of the user. For example, an officer's activity logs may show that there is a regular pattern between working place and home, such as "this user arrived to the working place at 9 a.m. everyday."

The patterns of user's daily lifestyle can be extracted as a multi-dimensional vector consisting of statistical metrics (sum, average, min, or max for every minute) of the collected data. Because our goal is to characterize a daily pattern for the user, we limit the data size to 24 hours while calculating features. In addition, we thought that durations shorter than one minute (e.g., every second) are not useful to represent a daily activity. These data vector patterns are used as input to the RNN model.

Learning RNN model

The RNN model is an artificial neural network, which has a directed cycle between units [11]. This model is appropriate due to the characteristics, where each unit of RNN has a time-varying activation with real-value. Figure 4 shows the RNN structure used to build the lifestyle model. In our model, each hidden layer will be calculated from each value of the given time series data T, where the number of time steps is n and i-th time step is Ti. The model used the dense function with ReLU (Rectified Linear Unit) when obtaining the output values in the last layer. By learning the three individual feature vectors (i.e., heart rate, step count, and burned calories), we can construct personalized lifestyle model for the particular user's daily living activities.

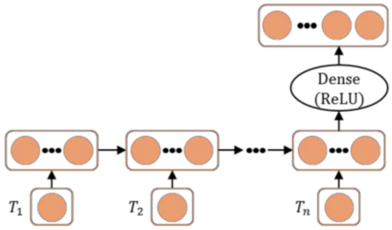


Figure 4 – RNN model to learn each time series data

Modeling individual's lifestyle

We obtain quality of lifestyle for the user by combining the collected activities of daily living and the outputs of learned RNN model. This RNN-based lifestyle model is personalized to the user's lifestyle. Therefore, each lifestyle model can be a baseline of the user's wellness, and can be utilized to make recommendations in the next stage.

Behavior recommendation

Next, our system have to decide adequate healthy behaviors based on the user's lifestyle model. Because the user's life depends on his or her own lifestyle patterns, considering context information of the user, such as location or time availability, facilitates to suggest proper healthy behavior to the user.

Figure 5 shows a flow chart illustrating procedures of behavior recommendation and adaptation to the user. This flow starts after constructing RNN-based lifestyle model for the user. First, we can obtain the user's upcoming activeness based on the lifestyle model. For instance, three types of values — heart rate, step count, and burned calories — can be predicted for the upcoming one hour from the current moment. We, then, check whether the predicted values of activeness are lower than the thresholds corresponding to each data type. If it is true, our sys- tem generates new behavior recommendation for the user to in- crease the amount of future activity.

Before suggesting new behavior, we consider the user's current location context to choose what activities are suitable. For example, walking around is sufficient if the user is just coming from the lunch near the workplace, and he or she must return to work soon. Moreover, we apply greedy policy for individuals to make a decision that provide healthy behaviors. The user can send feedback to our system corresponding to the behavior recommendations in the past. There are two types of feedback: one is a flag of satisfaction, and another is whether recommended behavior is finished or not. If the user responds that he or she is not satisfied with that particular recommendation, then parameters of greedy policy in the user's context are decreased. It means that the possibility of the behavior recommendation in the specific context is also reduced, and vice-versa. This adaptation process supports better personalization for the user.

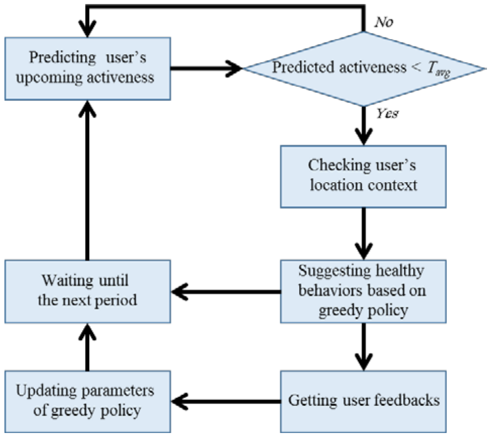
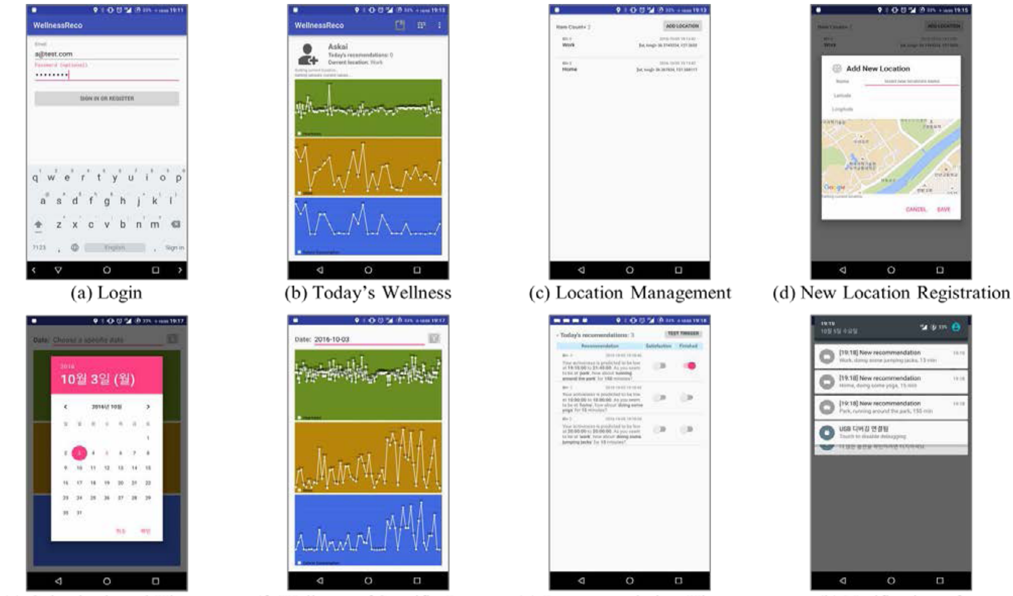


Figure 5 – Flow chart for suggesting appropriate behaviors to the user and adapting user feedbacks

Implementation of mobile wellness management system

In the previous two sub-sections, we explained the main steps of the wellness management system, RNN-based lifestyle modeling, and healthy behavior recommendation. Now, we describe the implementation details of our mobile app on Android platform. Figure 6 shows user interface snapshots for each functionality. The important functional features of the mobile app are as follows:

- Inquiry about the history of user's activeness for today or a specific date.
  - The user's activeness consists of heart rate, step count, and calorie consumption.
  - Each data of the activeness is depicted by a line chart individually.
- Recommend a healthy behavior periodically that can increase the user's wellness.
- Manage the history of activity suggestions.
- Support to get the user's feedback corresponding to activity suggestions.
  - There are two types of user feedback: a level of satisfaction regarding the prior suggestion, and another indicating whether a suggested activity is done or not.



(a) Login (b) Today's Wellness (c) Location Management (d) New Location Registration

(e) Calendar-based History (f) Wellness of Specific Date (g) Recommendation History (h) Notification of New Recommendation

Figure 6 – Snapshots of user interface for the mobile wellness management app on Android platform

Experimental Design

We have plans to collect target users' lifestyle data by using Jawbone UP3 wristbands as shown in Figure 1. We need sufficient log of data for participants over a period of long time, at least for a few months. For logging precise data from each participant in our experiments, we asked that they follow the instructions below:

- Participants have to wear the wearable device whenever possible during the experiment.
- Participants have to answer a questionnaire of psychometric assessment tools every day.
- Participants have to give two types of feedback for each recommendation—a *satisfaction level* and an *execution rate* of suggested activities.
- When adding a new activity manually, participants have to honestly insert actual information.

The satisfaction level consists of 6-point Likert scale as follows: *strongly satisfied* (3), *satisfied* (2), *slightly satisfied* (1), *slightly dissatisfied* (-1), *dissatisfied* (-2), and *strongly dissatisfied* (-3).

The execution rate R_e is obtained by

$$R_e = \frac{\sum_{i=1}^{N} e_i}{N} \times 100$$

time, at least for a few months. For logging precise data from each participant in our experiment, where N is the total number of recommendations, e_i means the i-th flag of execution, and e_i is 1 if the suggested activity is done, 0 otherwise.

The results of questionnaire and feedback is used to verify if our quality measure properly works.

Conclusion

Maintaining an individual's QoL is necessary in modern society, but it is very difficult due to the variety of lifestyles. In this paper, we proposed a mobile wellness management system for enhancing lifestyle quality based on analysis of time series data that is collected from wearable sensors. User's lifestyle patterns over time are extracted, and the RNN model is constructed by using the lifestyle features. Finally, our system makes suggestions of healthy behaviors underlying the learned RNN model depending on particular user's lifestyle.

In future work, we will conduct long-term experiment with several participants for collecting their activity logs of daily living and analyzing their lifestyle patterns in order to verify whether our management system has enough usefulness.

Acknowledgements

This work was supported by the Industrial Strategic Technology Development Program, 10052955, Experiential Knowledge Platform Development Research for the Acquisition and Utilization of Field Expert Knowledge, funded by the Ministry of Trade, Industry & Energy (MOTIE), Korea.

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