Life Record: A Smartphone-Based Daily Activity Monitoring System

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Abstract. In this paper, we propose a two-layered classification approach to effectively recognize the physical activities while the smartphone is placed at any four common positions on the body. Then we implement a Life Record app on smartphone that automatically classifies physical activities and records them as the personal life logs. For assisting users in comprehending their daily activities, the system also provides the visualization interface that shows the brief descriptions of their life logs.

We demonstrate that the system possesses less limitation to monitor daily activities that the users are not restricted to carry their smartphones in specific positions. Another major benefit of our system is to provide a complete overview of personal activities, which enhances the self-awareness of physical activity in our daily life through an intuitive visualization interface. Furthermore, analysis of life logs can also be applied in specific services or recommendation applications in the future.

Keywords: Activity monitoring · Life record · Physical inactivity · Pattern recognition · Data visualization

1 Introduction

Physical inactivity is one of the most important modifiable risk factors, and it causes unhealthy life habits such that most people spend their leisure time involved in sedentary pursuits. Due to this lack of physical activity, more and more people have become overweight (body mass index $\geq$25 kg/m^2) and even have become obese (body mass index $\geq$30 kg/m^2). Globally, in 2005, it was estimated that over 1 billion people were overweight, including 805 million women, and that over 300 million people were obese. By 2015, it has been estimated that over 1.5 billion people will be overweight [1]. Overweight and obesity, moreover, will cause increasing risk for various chronic diseases, such as diabetes, cardiovascular diseases, hypertension and cancer.

Y. Tan et al. (Eds.): ICSI-CCI 2015, Part II, LNCS 9141, pp. 380–385, 2015.
DOI: 10.1007/978-3-319-20472-7_41

Several commercially available devices, such as Fitbit One [2] and Fitbit Flex [3], Bodymedia [4], and Jawbone UP [5], have embedded these wearable sensors to provide daily activity monitoring, to compute caloric expenditure, and even trace sleeping status during the night. Although these can provide daily activity monitoring or specific exercise training, they need to be worn in a specific body position and are not popular for the general public.

In addition to hardware, smartphones also provide a developmental platform on which developers can easily design applications. Several studies [6-9] have proposed human activity recognition systems based on smartphones to facilitate long-term daily activity monitoring.

In this research, we use Android smartphones to collect daily activity data, so this system is applicable to individuals who own Android smartphones. Users can observe activity habits through their life logs from the visualizations on the smartphone application.

2 Related Work

Human Activity Recognition research mostly uses observation of human actions to obtain an understanding of types of activities that they perform within a specific time interval. Typical activities under consideration vary from mechanical process such as activities of daily living (ADL) to socio-spatial processes like meetings. To recognize the activities that occur in daily living, wearable sensors have been used to acquire the signals from different body positions intended to detect movements. Accelerometers have been the most commonly used device to recognize human activity during high performance in physical activity recognition (PAR) research. So far, almost all studies of PAR differ according to the type and number of activities identified and by the location, type and number of accelerometers used.

Wu et al. [40] proposed a system called SensCare, which was a semi-automatic lifelog summarization system for elderly care. SensCare fuses heterogeneous sensor information and automatically segments and recognizes user's daily activities in a hierarchical way. It combines unsupervised activity segmentation and activity recognition to segment an activity with the specific time period related to its occurrence. GPS data is fused with the activity segmentation to predict high-level daily activities.

Other studies referenced in [9-13] were all aimed at providing ubiquitous recognition systems used in long-term health care monitoring. In short-term supervised monitoring situations, large numbers of body-fixed sensors can be used to allow the collection of greater quantities of information, leading to very accurate assessments of movement; however, in long-term, unsupervised monitoring environments, subject compliance is essential if the system is to be used [14].

Human life models are useful in a variety of applications, such as the detection of abnormal behavior. They can also be used to analyze correlations between the regularity of workers' behavior and their levels of stress [15].

3 Material and Method

In this research, we develop a smartphone-based Daily activity monitoring system for measurement of daily activities in human life. We design a two-layered activity classification scheme to recognize the state of activity and the type of activity from the sensor signals of the smartphone. We implement the visualization of personal activity record and quantify the activities in daily life by the duration and the calories consumed from them.

3.1 System Architecture

The development process consists of two phases: (1) we first construct the two-layered activity classification scheme, which contains the data processing and model building. We collected the data from an accelerometer and an orientation sensor and extract the feature set as the input of the classification model. Then, the subset of features is selected to train the two-layered classification model. After the model building, it is tested with both the laboratory dataset and the real dataset; (2) we utilize the model to develop the Life Record app on smartphone for recording physical activities in users' daily life. We also implement the visualization methods on the app to provide an overview of personal daily activity. Finally, we analyze the activity patterns and the relationships from users' life logs for discovering the model of their daily life.

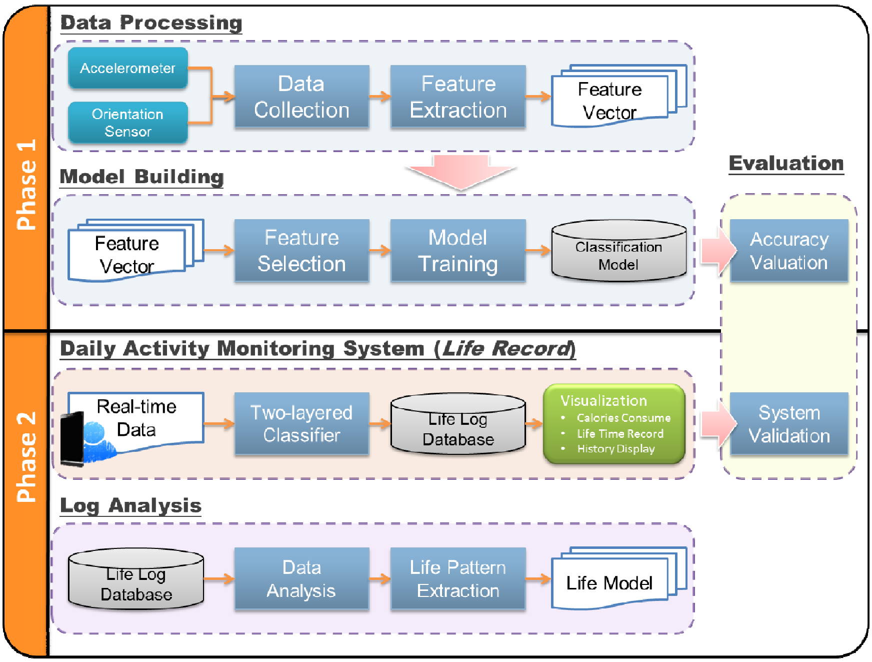

Fig. 1. System architecture

3.2 Two-Layered Activity Classification

We build a two-layered hierarchical activity classifier for recognizing the state and class of activity based on the sensor in smartphone.

Figure 3.4 shows the flow for building the two-layered classification model. First, a feature selection approach was used to pick out a subset of relevant features for the purpose of building a robust learning model before we built each classification model in the two-layered classifier. Then, the classification models were trained individually with the corresponding selected feature set. Finally, the classifier was constructed using the models for each layer, and it could be implemented for the Life Record app.

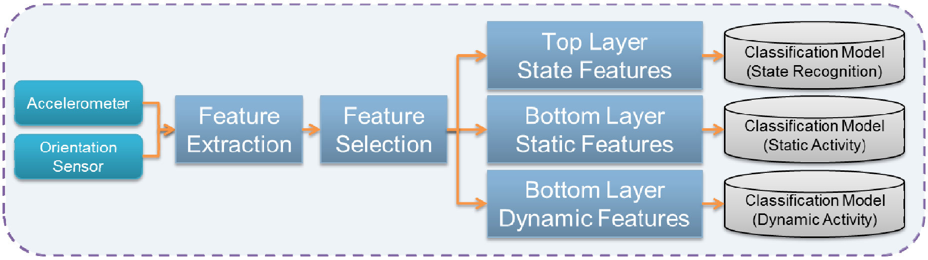

Fig. 2. Procedure for classification model building

3.3 Life Record App

We performed an evaluation of iHOPE. We invited twenty medical professionals and ten graduate school students to try out the system on a daily basis for two weeks, and they are asked to fill out the questionnaire for feedback after two weeks of practice. The participants all used the smartphone in a regular basis in their daily lives.

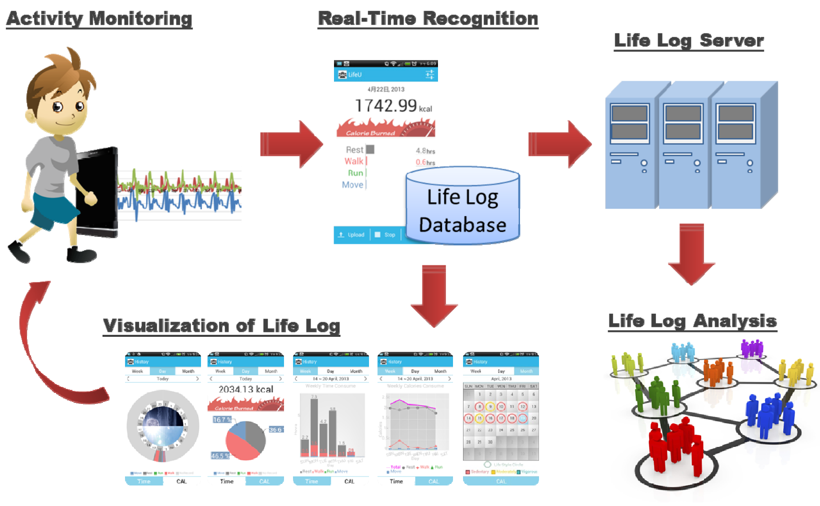

Fig. 3. Life Record scenario

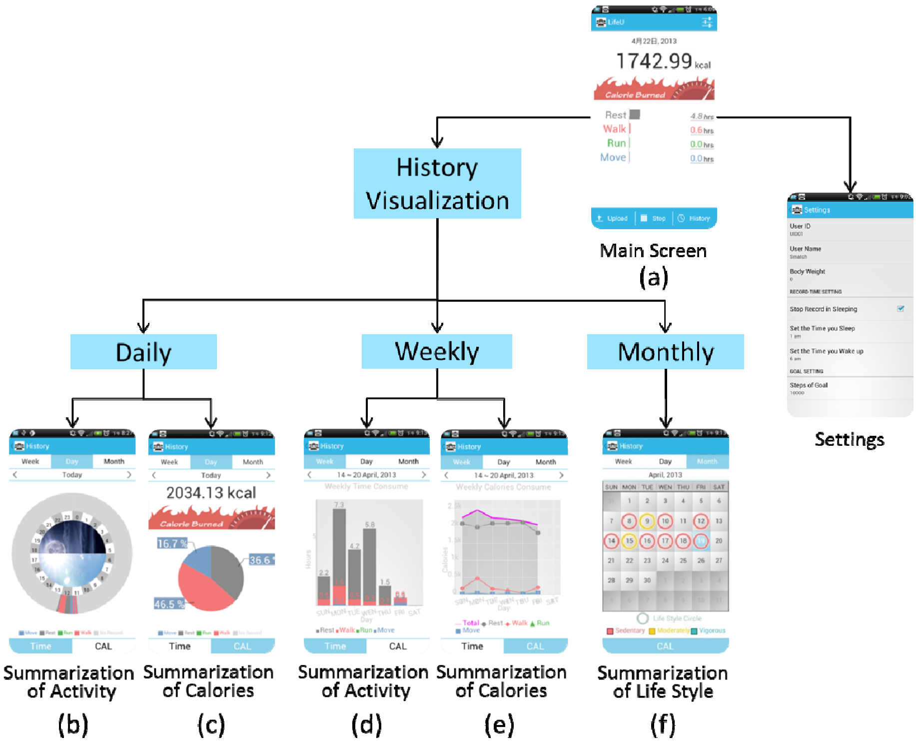

Fig. 4. GUI screens navigation flowcharts

4 Conclusions and Future Work

We developed the Life Record app on the Android smartphone because of its popularity, capacity for computing in real-time, and the graphical user interface that can show the visualization of the life logs used in this study. The outcome of the questionnaire providing participant feedback demonstrated the feasibility and usability of the system. The life logs recorded by the system were used to analyze personal life characteristics. In the end, we also proved the possibility of discovering relationships between users from the features found in the personal life logs.

An additional objective is to cooperate with medical care organizations and fitness experts to provide more professional and specific services, including such things as specialists' suggestion services, adaptive exercise plan recommendations, and combining social community platforms to share or compare with friends for encouraging participation in physical activities. These options could make the app more suitable for user demands.

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