"Fingerprints": Detecting Meaningful Moments for Mobile Health Intervention

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Abstract

Personalized and contextual interventions are promising techniques for mobile persuasive technologies in mobile health. In this paper, we propose the "fingerprints" technique to analyze the users' daily behavior patterns to find the meaningful moments to better support mobile persuasive technologies, especially mobile health interventions. We assume that for many persons, their behaviors have patterns and can be detected through the sensor data from smartphones. We develop a three-step interactive machine learning workflow to describe the concept and approach of the "fingerprints" technique. By this we aim to implement a practical and light-weight mobile intervention system without burdening the users with manual logging. In our feasibility study, we show results that provide first insights into the design of the "fingerprints" technique.

Author Keywords

Mobile persuasive technologies; mobile intervention; interactive machine learning.

ACM Classification Keywords

H.1.2. [Models and Principles: User/Machine System; I.5.4 [Pattern Recognition]: Applications.

Introduction
According to Fogg's behavior model [3], a person will perform a behavior only when he or she is sufficiently motivated, is able to and is triggered to perform the behavior. Therefore, even if the users have the motivation and ability, the proper triggers are necessary in health persuasive applications. As mentioned by Consolvo in [1], food logging application users always forget to log their food, which leads to incorrect analysis results. In many cases, the forgetting is caused by inappropriate or missing reminders. In the domain of context-aware mobile computing, the research focused on using different sensor data and machine learning algorithms to detect human behavior [4] or meaningful moments [6] for self-monitoring or interventions. Some research in the HCI community has explored interactive machine learning approaches to better involve the users' interaction into context-aware computing [2, 5]. But for mobile health intervention technologies, researchers seldom talk about adopting interactive machine learning. In this work, we explore how to apply interactive machine learning strategy into context-aware computing for mobile health interventions.

To this end, we present here the "fingerprints" technique, which is a metaphor for human behavior routines or patterns (e.g., going to work, going to the cafeteria, or drinking water). In this work, we use a three-step approach to design a system in order to not only enable highly personalized and timely interventions but also to reduce the burden on the user of logging data. Our work is based on two assumptions: 1) people have daily routines which can be detected by their mobile devices 2) these routines carry potentially relevant "fingerprints" to trigger behavior change. In our feasibility study, we show results that provide first insights into the design of the "fingerprints" technique.

Scenario Description
To better present the "fingerprints" technique, we apply it to an example of health persuasive application. This scenario illustrates the process of how we make human routine detection and intervention with the interaction of the users:

One of the authors always has much meat in his lunch, which is unhealthy. Therefore, he wants to get an intervention when he goes to the cafeteria to remind him to eat more salad rather than meat. He starts to use the "Fingerprints" application on his smartphone. In the first week the application runs in the background and collects the data automatically. Then the application asks him to name the found behavior patterns. He selects the one "from the office to the cafeteria" and names it to "Going to lunch." Meanwhile he adds an intervention item in the application. After that, he gets notifications to remind him to eat more salad instead of meat when he goes to the cafeteria.

Concept and Approach
We design our approach based on three considerations: applicability, complexity, and the burden on the user. The data used in our method includes the location (from the GPS or the network), the Wi-Fi SSID (the name of the Wi-Fi provider), the physical activity (walking, running, still, tilting, on a bike, on a vehicle, or on foot) and the time stamps. We model each "fingerprint" as a sequence of state transitions. Each state is described as a collection of sensor data with the time stamp, e.g., {Location, Wi-Fi connection, Physical Activity, Time-Stamp}.

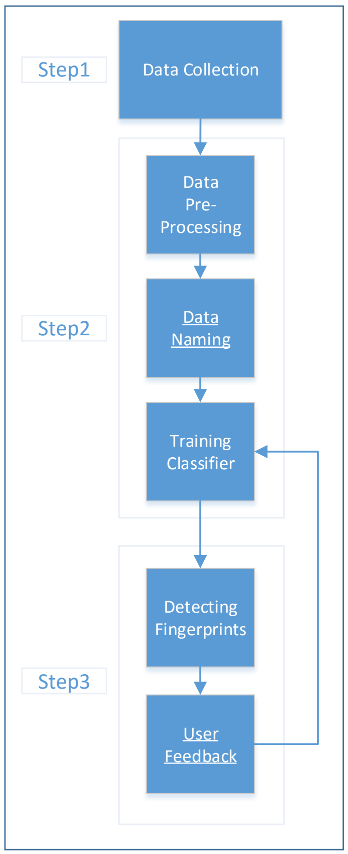

Figure 1: The workflow of the "fingerprints" system. Step 1 is data collection; step 2 is "fingerprints" generation; step3 is real-time detection of the "fingerprints."

To make the system energy-efficient, instead of calculating in a fixed time interval with a fixed time window, we collect and process the data only when the state changes. The reason is that for persons like students or office workers, the smartphones are not often in motion. Compared to a time interval-based data collection method, the system avoids calculating redundant data.

Most importantly, we want to reduce the burden on the user of manually logging activities to train the classifier. To this end, we do not simply adopt the traditional machine learning strategy of other researchers in the field [5], which asks users to label the data repeatedly. Instead, we first collect sensor data for a period of time, followed by a data pre-processing step to find potential "fingerprints." These two steps are executed automatically. The users can then name the potential "fingerprints" in one setting, whereby a collection of labels are gathered for the classifier training.

In the Data Pre-Processing step, we regard the task of finding potential "fingerprints" as a common substring problem. We use the generalized suffix tree based algorithm to solve the problem. The system generates the string by encoding the location data. After users naming the potential "fingerprints", the system divides each named "fingerprint" into three sections (the beginning, the middle, and the end) and then uses decision tree model to train the classifier.

In the step of Data Naming, the user is provided with an interface to show the found "fingerprints" and asked to name the activities they are interested in. After labeling the "fingerprints," the classifier is trained with the labels. In next step, the system starts to detect the "fingerprints" and to provide interventions to the users. The classifier is updated according to the users' feedback. The data is continually collected and activities matching the "fingerprints" are labeled when they appear. The workflow of the "fingerprints" system is shown in Figure 1.

Feasibility Study

We conducted a feasibility study to collect data for offline analysis. We developed an android application (see Figure 2) to collect the data as described in the previous section. We invited three university students as the participants.

The study had three sessions, including a participant survey session, a data collection session, and a data validation session. In the participant survey session, we asked all the participants to describe their daily routines in a questionnaire by email. Based on their answers, we selected three common routines and incorporated the functionality of logging these routines in the application. In the data collection session, the participants installed the application on their smartphones and started the background service. This session lasted for four working days. We allowed the participants to stop the service at any time for the sake of privacy. We also asked the participants to manually log the three pre-defined routines by pressing a "START LABEL" button and a "STOP LABEL" button when they start and stop a routine, respectively. Manual logging is not included in the workflow we designed as shown in Figure 1. We added this part in the feasibility study in order to get ground truth data for evaluating the results of our algorithm. In the data validation session, we asked the participants to validate their logging data by checking if the location information and their logging data are matched.

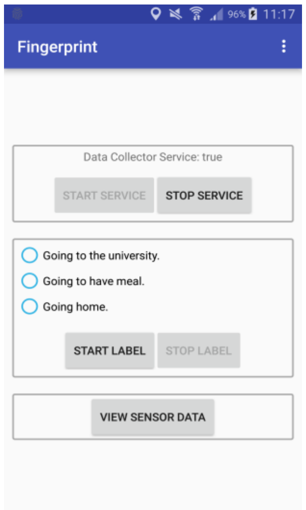

Figure 2: The user interface of the prototype application.

	R1	R2	R3	Data Entries
P1	8	13	8	2769
P2	4	9	4	2304
P3	0	12	0	327

Table 1: The numbers of detected appearances of three routines (R1, R2 and R3) and the data entries of each participant (P1, P2 and P3). R1 is "going to the university"; R2 is to "going to have a meal"; R3 is "going home".

From the location data, we filtered out the empty entries (no location provided). Then we processed the data to find the potential "fingerprints". We ignore patterns with less than four appearances, because daily routines should appear four times at least in four days. The results are shown in Table 1. Our method detected all three routines for Participants 1 and 2. However, for Participant 3, only routine 2 was detected. After reviewing the raw data, the cause was found to be that number of data entries for this participant to be much smaller than the others.

From the user logging data, we also found that the participants always forget to label our pre-defined routines. This is consistent with the related work [1], which is a good reason why we cannot rely on the users' labeling to train the classifier at the beginning of our workflow.

Conclusion and Future Work

In this paper, we present the "fingerprints" technique to support mobile health interventions by detecting users' daily routines and meaningful moments. We show our concept and approach by which we aim to make our system practical, light-weight and less burden on users of manual logging. In our feasibility study, we tested our assumptions with a small number of participants using the sensor data from stock smartphones.

The results of the study were promising and based thereon, we will implement our whole workflow and conduct the evaluation, especially from the perspective of user experience.

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