Poster: Checkpoint-and-Remind (CAR) Method for Balancing the Users' Burden and Users' Control in Collecting the Annotated Mobility Data

Mahardeka Tri Ananta
National Chiao Tung University
Hsinchu, 30010, TW
deka.eed07g@nctu.edu.tw

Yung-Ju Chang
National Chiao Tung University
Hsinchu, 30010, TW
armuro@cs.nctu.edu.tw

Chih-Hsin Lin
National Chiao Tung University
Hsinchu, 30010, TW
neu.cs07g@nctu.edu.tw

Hsiu-Chi Chang
National Chiao Tung University
Hsinchu, 30010, TW
wbest601.cs05g@g2.nctu.edu.tw

TAICHI'20,, October 23–24, 2020, Taipei, Taiwan
ACM 978-1-4503-6819-3/20/04.
https://doi.org/10.1145/3334480.XXXXXXX

Abstract

The use of mobile crowdsourcing technology for collecting continuous human-labeled data increases user burden. Accordingly, we propose a hybrid method that combines a Participatory sensing (PART) and Context-Triggered Experience Sampling Method labeling (ESM) called Checkpoint-and-Remind (CAR) to collect mobility activity data. CAR offers the benefit of user control and is less burdensome in recording continuous activity data. It is also equipped with the context-triggered ESM module as a back-up component to record the trip activity in case the user does not do a checkpoint and to remind the user of labeling the trip activity. We performed a field study by involving 30 participants within 15 weekdays. Our results exhibited that CAR has moderate controllability and less burdensome than PART, while ESM is the least burdensome due to its context-triggered mechanism. In the future, our work is investigating the number of annotated mobility data of these three methods and user behavior when using the CAR in depth.

Author Keywords

Human-labeled; human-annotated, ground truth; user burden; mobile crowdsourcing; transportation

Figure 1: The top figure depicts the recorded activity timeline page; the bottom one depicts the activity labeling and annotation page

CCS Concepts

•Human-centered computing → Human computer interaction (HCI);

Motivation

Providing high-quality and useful human-labeled and human-annotated data for the preliminary phase of the development of machine learning-based human activities classifier. Therefore, these data could be used as the training data and testing data to build this reliable human activities classifier system.

Purpose

Inspired by [2] which reported that Context-triggered ESM produced high-quantity labeled activity recording data due to its automated data recording feature and reminder mechanism, but the inaccurate detection system occasionally leads to annoy the user and decrease the users' compliance. On the other hand, PART produced higher precision and completeness of labeled activity recording data though it requires more users' effort since the absence of automated recording and reminder mechanism. Also, PART leads to more burdensome since the user needs to remember to record their activity. As *user control* and *user burden* are two critical factors of collecting continuous human-labeled data. Thus, we consider the balance of relaxing user burden and granting user control [2] while sustaining the label and annotations compliance by developing CAR, a hybrid method for collecting daily continuous annotated activity data [1].

Method

We developed Labeling Study App [1], the android based research app for data collection that includes three different methods, i.e. Participatory (PART), Context-Triggered Experience Sampling Method (ESM), and Checkpoint-and-Remind (CAR). Our app has two major parts which are annotation and recording. As depicted in Figure 1 (top), the first part displays the timeline page of the detail of user activities during their trip (e.g. on foot, on the bicycle, in the vehicle, and static) which are recorded by the app. While, the second part (see Figure 1 bottom) is used to annotate and label their activity during their trip including start-end time, type of activity, goal, special event occurred along their trip (if any), and labeling their static activity type by choosing a place on a map.

In PART condition, Users are asked to fully control their activity recording and annotation by themselves. Initially, they can select their type of upcoming activity (see Figure 2 left) and later start to record their trip by pressing the start button and stop button to end their trip (see Figure 2 right). Afterwards, it will be listed on the activity timeline page for labeling and annotation.

In ESM condition, the user activity will be detected by the app automatically. Specifically, we equipped it with google activity recognition API to detect user mobility activity and added a finite-state machine to determine a user's transportation mode label. Whenever the app detects a user transport mode, it records the activity and prompts the notification to the user (see Figure 3 left). The notification aims to remind the user that they have a new activity recorded on the timeline page to be labeled.

In CAR condition, the user can either manually record their trip activity or automatically record their activity via app. In this condition, If they thought there will be a transition of different activities occurring sequentially then they need to perform "checkpoint" (see Figure 3 right) at a certain switching point. The Checkpoint here is defined as a term for checking the activities-switching point. As a result, the app switches the activity which means stop the recording of

Figure 2: The left figure depicts the activity selection page in PART; the right one depicts the activity recording page in PART

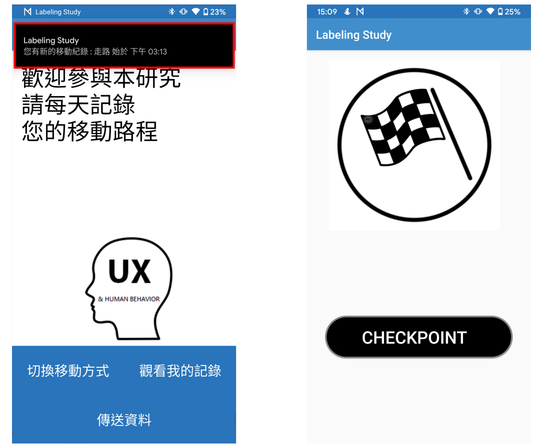

Figure 3: The left figure depicts a reminder notification in context-triggered ESM condition; the right one depicts the activity checkpoint page in CAR

ongoing activity and start to record the next different activity. While, If they forget to do checkpoint at the switching point or the app detects a switching to the next activity before they checkpoint then, the app waits for a minute for them to do checkpoint. If they still do not checkpoint in a given waiting time then the app performs context-triggered ESM functionality to record that new activity automatically and sends a notification to remind them about annotating their activity. At the ground truth reconstruction phase, we compare the captured photos and participants' travel data by considering the start time and end time of each trip.

Current Results

Currently, based on the NASA Task Load Index (NASA-TLX) measurement, we proved that the user burden level of the CAR method (M=3.93) is lower than the PART method (M=4.54), while the Context-Triggered ESM (M=3.11) has the least user burden level due to its context-triggered mechanism. In addition, the CAR method offers moderate control. This result confirmed that the combination of human sensing and context-triggered sensing could reduce the human effort in labeling and annotating the continuous activity data.

Future Plans

Henceforth, we plan to do a deeper analysis of the quantity and quality of collected mobility data by these three methods. Also, we are going to investigate the user behavior while labeling and annotating using the CAR method since it leads to increase the user's laziness.

REFERENCES

[1] Hsiu-Chi Chang, Yung-Ju Chang, Mark W Newman, and Chih-Hsin Lin. 2020. Combining Participatory and ESM: A Hybrid Approach to Collecting Annotated Mobility Data. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–7.

[2] Yung-Ju Chang, Gaurav Paruthi, Hsin-Ying Wu, Hsin-Yu Lin, and Mark W Newman. 2017. An investigation of using mobile and situated crowdsourcing to collect annotated travel activity data in real-word settings. *International Journal of Human-Computer Studies* 102 (2017), 81–102.