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# Interruptibility Map: Geographical Analysis of Users' Interruptibility in Smart Cities

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***Abstract*—Investigating users' interruptibility as an indicator of his/her attention status has been essential in recent pervasive computing where the users' attention resources get scarce against ever increasing amounts of information. In this paper, we address research problems related to the users' available interruptibility, their physical activities, and their current locations and situations. We propose the "Interruptibility Map", a geographical tool for analyzing and visualizing the user's local interruptibility status in the context of smart city research. Our map describes where citizens are expected to feel more or less interruptive against notifications produced by computing devices, which are known to have negative effects on work productivity, emotion, and psychological state. We conducted a continuous analysis from our previous research and a new additional in-the-wild user study for 2 weeks with 29 participants to investigate the relationship between one's interruptibility and their locations and situations. As a highlight of our findings, we found certain pairs of user activity change and a location that showed better interruptibility to users, such as an activity change of "when user's riding car(bus) stops" in the bus commute situation.**

## I. Introduction

As versatile types of mobile and wearable devices (such as smartphones, tablets, smartwatches) have been penetrating the global share, and the number of web services and applications invented are drastically increasing, thus an ever amount of information has been provided to us. We are getting numerous amounts of notifications informing of new text messages, schedule reminders, updates on the social networks, or advertisements. Meanwhile, since the human attention is a limited resource [1], [2], users are not able to handle all "interruptive" notifications coming from the background of their primary tasks, experiencing "divided attention" [3]. Previous literature has found that there are various types of negative effects on divided attention caused by the interruptive notifications, such as for work productivity [4]–[9], emotion [8], and psychophysiological states [5].

To avoid this information and interruption overload, one of the considered approaches is to deliver a notification at a certain timing called the "breakpoint" [10], the boundary of the user's activities that has been found to reduce the user's cognitive load and mental burden against interruptions. In our previous research [11], we proposed a system for improving the answer rate against interruptive push notification delivered into the users' smartphones, by detecting the user's **physical activity breakpoints** [12], such as when a user stops walking (from "walk" to "stationary") or starts running (from "stationary" to "running"). We utilized activity recognition API which was recently provided by the major mobile operating systems, such as iOS and Android, and investigated the interruptibility of each activity transition types (e.g. "from stationary to walking") extracted from the API. In comparison with the "deliver immediately" style conventional notification delivery scheme, our evaluation result revealed the effectiveness of breakpoint-based notification delivery with a higher response rate and faster response time.

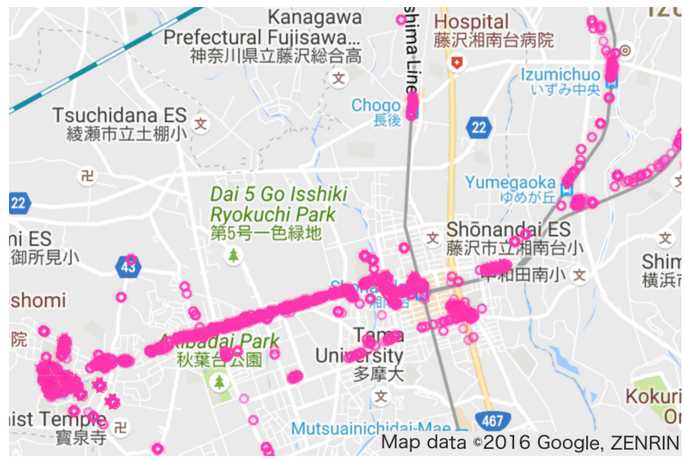


Fig. 2. The screenshot of "Interruptibility Map"

However, in the continuum of our research after the previous experiment, we came to observe a significant new research opportunity in the investigation of user's affective statuses including interruptibility in the physical space. Firstly, it is not clear **which types of physical activity breakpoints occur in different locations**. If we can detect particular locations with a trend of specific breakpoint occurrence that increases the user's interruptibility, we can utilize such knowledge for further user support. Furthermore, it is also not clear **if users' interruptibility, even when it is based on the same type of breakpoint timing, can result in different values in different locations and situations.** In this paper, we particularly focus on investigating on these questions in the context of smart city research [13]–[15], proposing and using the "Interruptibility Map" (Figure 2), our novel affective visualization and analytics tool on the geographical map.

Our interruptibility analysis with Interruptibility Map showed that (a)the occurrence rate of breakpoint types are

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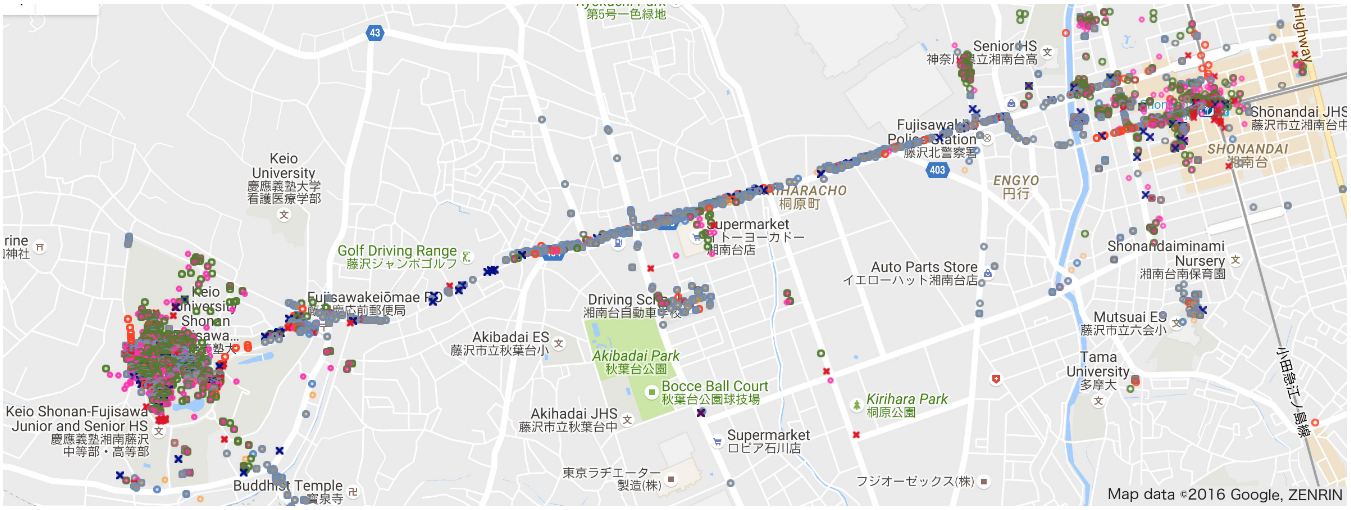


Fig. 1. Interruptibility Map

relevant to the geographical locations, and (b)the interruptibility of particular breakpoints can be affected by locations and situations. As a result, we successfully found some good pairs of breakpoint types and the location that considered to be a good timing to interrupt the users, such as "from automotive to {stationary,automotive}" in the bus area.

The contribution of this paper is three-fold. Firstly, we show our deeper analysis of the previous experiment by separating into 3 situations. Secondly, we propose the concept, designing and implementation of the Interruptibility Map. Lastly, we investigate how the interruptibility of breakpoint types differ by location.

In the remainder of this paper, we describe the interruption overload problem caused by notifications from computing systems in Section I. Then we will describe our previous research and the next research challenges we are interested to tackle in Section II. Section III explains about our concept of the "Interruptibility Map", and the continuous analysis and additional experiments we have conducted to solve our problems in Section IV. Finally, we conclude this paper in Section V.

## II. Interruptibility at Activity Breakpoints

This section firstly describes the results from our previous experiment and specifies research challenges which are to be addressed in this paper.

### A. Results from The Previous Experiment

In our previous research, we investigated the correlation between the breakpoint types and the interruptibility against interruptive notifications, by conducting an in-the-wild user study with 28 participants for four days collecting 20660 breakpoints. Each participant experienced "immediate delivery" style notification (which emulates the conventional notification style) for two days and "breakpoint detection"-based notification delivery for two days. As a result, the breakpoint-based notification delivery resulted in higher user response rate (58%) compared with the conventional immediate-delivery scheduling (50%).

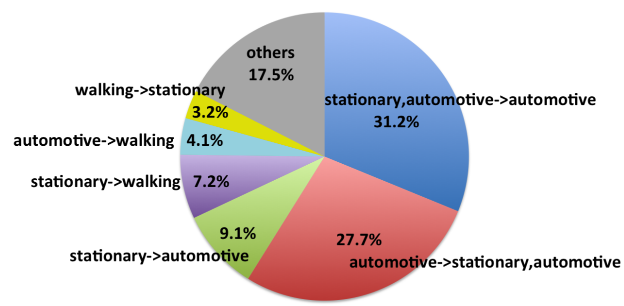


Fig. 3. Occurrence rate of each breakpoint type

Moreover, we found some breakpoint types that particularly contribute to higher user interruptibility while some other types showed a negative impact. (Figure 4). For example, "from walking to stationary" breakpoint type improved the response time while "from stationary to walking" breakpoint type required more time to open the notification. We hypothesize that, when people start walking, their attention will become less available since they need to face forward, causing difficulty in interruption.

Also, in the paper we discussed the occurrence rate of each breakpoint type (shown in Figure 3) and found that the top 2 breakpoint types, related to "automotive", filled 60% of the total number of detected breakpoints. Figure 2 is a map with plotted markers which indicate the breakpoint type "from {stationary,automotive} to automotive". We figured out that most of markers of these 2 types tend to appear intermittently on the roads and railroads.

### B. Next Research Challenges

From the discussion above, here we specify two next research challenges to be addressed in this paper. The first

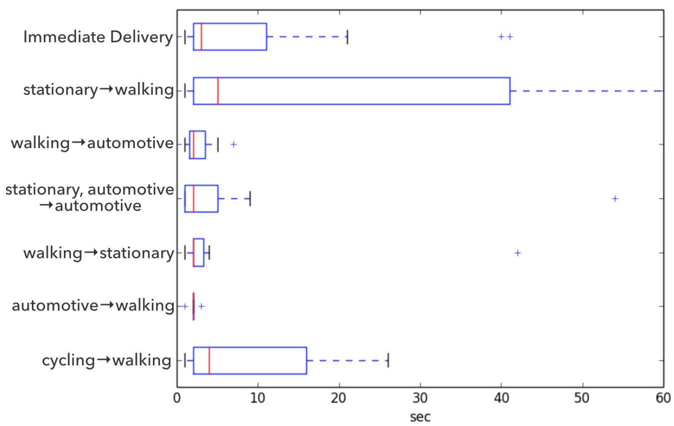


Fig. 4. Boxplot of response time for each breakpoint types

challenge is the investigation of **what types of physical activity breakpoints occurs in different locations.** Some existing literature showed that the user's "interruptibility" is different in different locations [16]. (e.g., the bus stops, subway stations and the parking lots are more interruptive than the movie theater or the library.) This result brought us to the hypothesis that the type of physical activity breakpoint may have a correlation with the venue location.

The second challenge is **the investigation of users' interruptibility in various types of breakpoints over different locations and situations.** Even on the same type of physical activity breakpoint, resulting user interruptibility value may differ depending on the locations and situations. For example, the same "from walking to stationary" breakpoint type may result in different interruptibility in different locations, such as in the train station and the office. For another example, the same "from automotive to stationary" type breakpoint may reveal different interruptibility in different situations, such as user commute in the train or that in the bus. (Currently the activity recognition API in smartphone platforms [17] does not distinguish the differences between trains and cars. It returns "automotive" in both situations.)

## III. Interruptibility Map

Considering the research problems outlined, we propose "Interruptibility Map" as a new analysis and visualization infrastructure of users' interruptibility. The concept of Interruptibility Map is actually our first step towards the realization of conceptual "Affective Map" particularly in the context of smart city research [13]–[15] where the local city people's affective status, including interruptibility, will be safely shared, analyzed, visualized, and used for various types of smart city applications.

Figure 5 illustrates the concept and the architecture of the Affective Map. On the local citizens' mobile devices, various types of affective data (including interruptibility [12], [18]) are sensed, followed by edge computation for privacy protection [19]. The sensor data with user's export permission will be uploaded to the distributed heterogeneous sensor network [20] of the area and stored in storage. Affective Map (1) analyzes

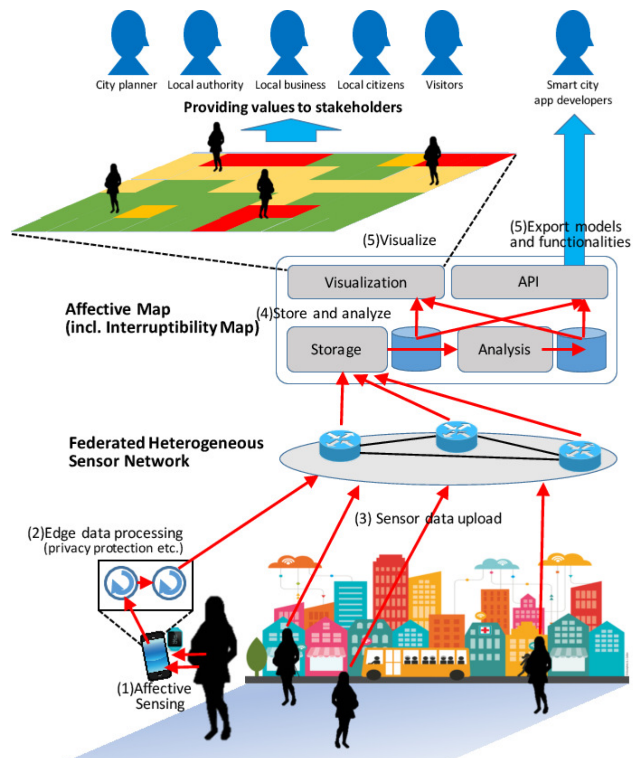


Fig. 5. Concept of Affective Map

the collected data and generates the results in the geographical space basis, and (2) visualizes/exports the results for various types of applications.

Key expected use cases of Affective Map are to evaluate what the government, businesses, or private organizations have devoted to the cities. For example, they can use the map to evaluate if the park brings people better quality of life (QoL) as planned, if the new expressway has relieved citizen's frustration, or if the new office is in a good location to prevent depression. Affective Map is the tool that allows us to visualize the city's mental state.

On visualization, we currently use the markers and the heatmap meshes on the geographical map, which is one of the most common data analysis methods. Showing the data in the form of a map gives us an intuitive understanding of the characteristics of the data, rather than the report making use of various technical terms, or lingo. Specifically in case of our current "Interruptibility Map" prototype, the map describes the locations that resulted lower frustration and cognitive load against the notification. The map indicates where the users are expected to feel more or less interruptive against notification produced by computing devices.

## IV. Analysis

In this section, we will detail our continuous analysis from previous research on breakpoint occurrence in different locations, followed by the second investigation on interruptibility in different locations and situations

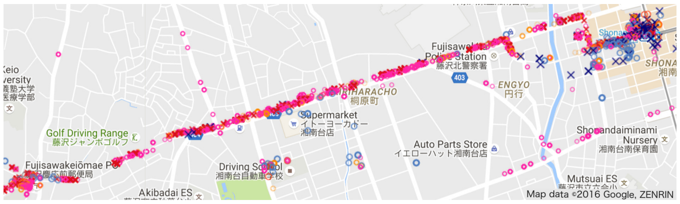


Fig. 6. Map of bus area

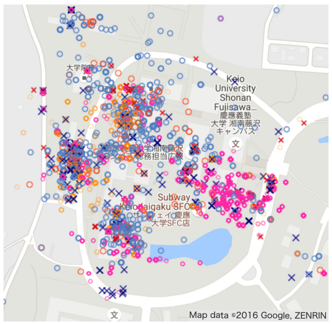


Fig. 7. Map of university campus


Fig. 8. Map of railroad area

## A. Breakpoint Occurrence in Different Locations

*1) Approach:* One of our research goals is to study the breakpoint occurrence tendency in different locations. As previously mentioned, we found that some types of physical activity breakpoint significantly increase user's interruptibility. However, if those breakpoint types rarely occur in the users' real environment, that means that there is very little opportunity to deliver notifications to users in such ideal timings. To analyze how the occurrence of various types of breakpoints vary over different locations, we decided to separate the data from our previous experiment into three locations as follows.

- University Campus (Figure 7)
- Commuting (Bus) (Figure 6)
- Commuting (Train) (Figure 8)

Our university campus is located approximately 20 minutes away from the nearest train station by bus. Most of the students take trains (about an hour) and a bus to commute to the university campus. We distinguished the university campus and bus route area (an area between the campus and the bus terminal at the train station) by picking the data points in a specific geographical area on the map. Moreover, we did the same geographical-area based data scoping for 4 major railroad routes in the local area to distinguish the breakpoints in the train commute situation (geographically plot on the railroad area).

*2) Results:* Figure 9, 10, 11 are the resulting pie charts indicating the occurrence rates of different breakpoint types in the university campus, the bus area, and train railroad area. For all, top two breakpoint types that occurred the most frequently were (1) "from {stationary,automotive} to automotive" and (2) "from automotive to {stationary,automotive}". The total occurrence rates of these two breakpoint types were 50.3% in the campus, 77.1% in the bus area, and 49.0% on the railroad. Moreover, the total occurrence rates of all breakpoint types containing "automotive" were 59.5% in the campus, 84.6% in the bus area, and 73.5% on the railroad.

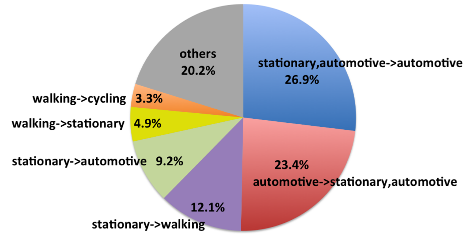


Fig. 9. Occurrence rate of breakpoint in the campus

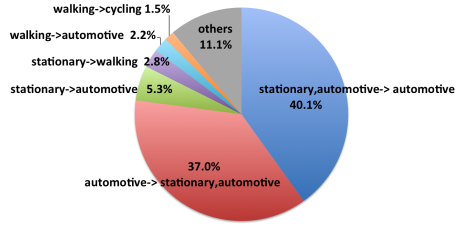


Fig. 10. Occurrence rate of breakpoint in the bus area

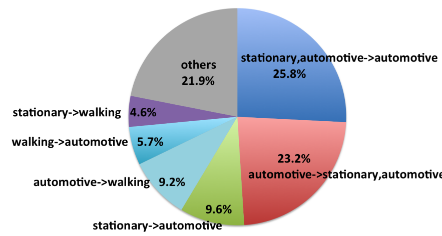


Fig. 11. Occurrence rate of breakpoint on the railroad

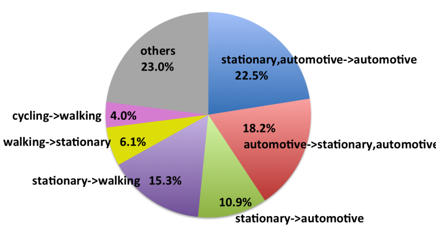


Fig. 12. Occurrence rate of breakpoint in the campus excluding bus stop area

We observe that the ratio of these two types of breakpoints fills approximately three quarters of the bus area, which is much higher than the ratio on the railroad. This means that the users would face more "stopping" and "moving" in the bus more frequently (possibly due to the traffic signals or traffic congestion) than on the railroads (temporarily stopping at the stations).

Figure 13 is a boxplot illustrating, on each breakpoint type, the distance to the nearest traffic signal in the bus area. We can see that the both "from {stationary,automotive} to automotive" and "from automotive to {stationary,automotive}" have shorter boxes (ranging from the 25 percentile to 75 percentile) than others. We believe this illustrates the fact that these breakpoint types are observed in very limited locations in certain degree of short distance from the traffic signals while other types are observed in much wider areas in terms of the distance from the signal.

Also, we are surprised that the breakpoint breakdown in the

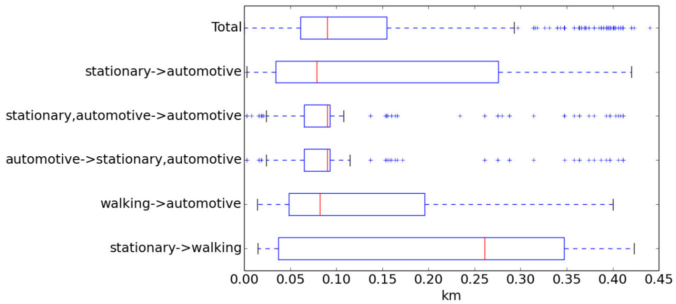


Fig. 13. Boxplot of distance to the nearest signal

university campus contains lots of "{stationary,automotive}" and "automotive" labels, too. In addition to Figure 9 that counted the data in the whole campus area, we calculated the breakpoint breakdown for the university campus excluding the bus stop in the campus (Figure 12). Even in this case, we see that the top two breakpoint types are the same. While it is natural to observe "{stationary,automotive}" and "automotive"-related breakpoints in the bus, railroad, and the bus stop areas, the cause of observing them in the middle of the university campus (such as near the classroom, laboratory buildings and cafeteria) is not clear. Although we need further investigation on this, it could be a limitation for this research since we are relying on the product activity recognition API provided by the the smartphone platform to detect users' activities.

### *B. Investigation of the Interruptibility in Locations*

Our second study is to investigate users' interruptibility in various types of breakpoints over different places. Having this objective, we conducted another in-the-wild user study specifically to validate if different locations and situations influence the resulting user interruptibility value even in cases with the same types of underlying physical activity breakpoints.

*1) Experiment:* We conducted an in-the-wild user study with 29 participants. They are undergraduate and graduate students (20 male and 9 female) of ages 18–26. The study duration was 14 days.

In this experiment, we particularly chose two breakpoint types, **"from {stationary,automotive} to automotive" (type 1)** and **"from automotive to {stationary,automotive}" (type 2)**, the top 2 most frequently observed breakpoint types in the previous experiment.

We installed our iOS application into the participants' personal iPhones. During the experiment, the participants were required to annotate the ESM questionnaires when they received a notification on their smartphones. When the user clicked the notification, the ESM screen was presented. The users were asked to answer on his/her interruptibility with 5-point Likert scale.

During 14 days, each participant experienced the following two notification delivery modes for 7 days each.

- Random-timing delivery: Notifications delivered at a random timings, emulating the conventional notification delivery.
- Breakpoint delivery: Notifications delivered when the targeted breakpoint was detected.

The notifications were issued during 8:00am to 10:00pm daily, with the daily maximum number of notifications of 10 (5 times for each delivery mode). The minimum notification interval was 20 minutes.

*2) Results:* Table I shows the average score of ESM questionnaire in different locations. The annotation scores answered in type 2 breakpoints were much higher than those in type 1 breakpoints, in the university campus, bus area, and railroad. In other words, we can observe that type 2 is better timing to interrupt rather than type 1.

Comparing the interruptibility between locations, the bus area is the best place to interrupt and the university campus is the worst for both type 1 and type 2. Especially, type 2's score in the bus area was 4.5. This is considered to be very opportune timing to deliver a notification, considering that the number is on a 5-point scale.

Figure 14, 15 are boxplots representing the response time of each breakpoint types in different locations. First of all, we can see that the bar width of the bus and train are quite different between breakpoint type 1 and 2. The response time for type 2 in bus area is quite fast and looks like very opportune timing to interrupt. As mentioned, this particular situation (and breakpoint type) also scored the highest interruptibility score in our experiment.

The railroad was the location in which different results are observed between 2 breakpoint types. We can see that the box is narrow on type 1, but is quite wide for type 2 (Actually the maximum value reaches up to about 400 seconds, but we decided to narrow the figure up there for the sake of visibility.)

*3) Discussion:* From these two observations, we can confirm the differences in the users' attention in different situations (bus and train). In the train, users' attention will be scarce when the train stops at the station, but soon will be able to be interrupted after the train departs. Possible reasons for this is that, when the train stops at the station, people's attention tend to be consumed more in the physical space, checking if the station is his/her destination, or looking for seats available. Once the train leaves the station, users are considered to become interruptible since they do not need to worry about next stop for a while, in certain degree of stabilized running speed of the train.

On the other hand, situation in buses are considered to be quite different. When a bus stops frequently at a signal or in the middle of traffic, passengers do not need to concern themselves with things such as the destination or seats since the bus has not reached to the next bus stop. Thus, we consider those facts resulted better interruptibility in type 2 breakpoint. When the bus starts, we have another different situation from the train case. Since the bus is in the middle of road traffic, passengers are not really sure when it physically speeds up, down, or stops next. This kind of situational difference is considered to result in lower interruptibility in breakpoint type 1.

TABLE I
AVERAGE VALUES OF ESM SCORE FOR LOCATIONS

| | Total | University | Bus | Train | Others |
|---|---|---|---|---|---|
| Avg. of ESM score (type1) | 3.0 | 2.3 | 3.6 | 2.5 | 3.4 |
| Avg. of ESM score (type2) | 3.1 | 2.8 | 4.5 | 3.0 | 2.9 |

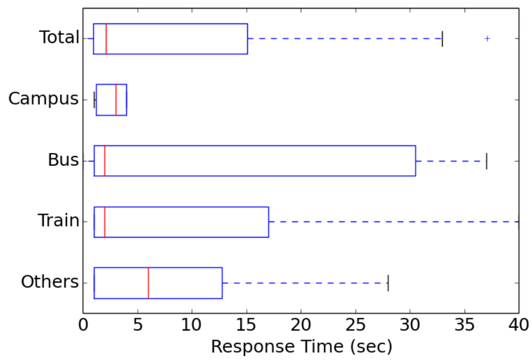


Fig. 14. Boxplot of the response time of type 1

## V. CONCLUSION

As the results of continuous analysis from our previous research and additional 2 week experiment with 29 participants, we showed that the occurrence rate of breakpoint types depends on the geographical locations. Furthermore, we confirmed that the interruptibility of particular breakpoints can be changed in the different locations. We found some pairs of breakpoint types and locations , such as “from automotive to {stationary,automotive}” in the bus area, are really good timings to interrupt the users. For our future work, collection of more extensive amounts of interruptibility data clearly would be our major future challenge. Beyond our first prototype, currently we are building the next prototype of the “Affective Map”, combining our infrastructure on interruptibility sensing [12], [18], edge privacy protection [19] and sensor network [20].

## ACKNOWLEDGMENT

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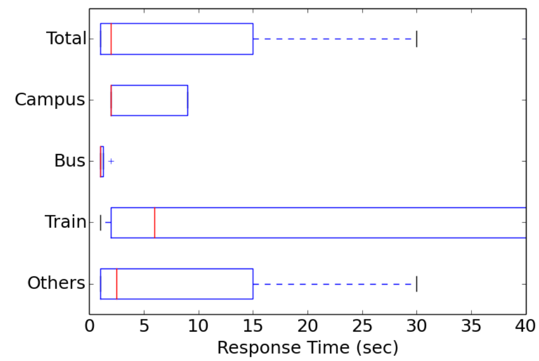


Fig. 15. Boxplot of the response time of type 2

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