Preliminary Investigations About Interruptibility of Smartphone Users at Specific Place Types

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Ubicomp/ISWC'16 Adjunct, September 12–16, 2016, Heidelberg, Germany
 ISBN 978-1-4503-4462-3/16/09...$15.00
DOI: http://dx.doi.org/10.1145/2968219.2968554

Abstract

Smartphones are our ubiquitous, personal, wearable companions. Though, apart from their smartness and usefulness in our everyday lives they can cause displeasure. They allow us to be connected to a load of people and with a vast amount of apps - all of them requiring our attention. There is a growing need for a smart management to not be overwhelmed by the flood of information and notifications. A first step in that direction is to identify detectable contexts in which interruptibility is very high or low.

In this paper, we present results of a survey taken by 68 persons. Within the survey, we assess how much smartphone notifications interrupt and disturb users at a specific location. The locations were selected based on the places that can be recognized by the Google Places API. This shall serve as a basis for future interruptibility research.

We noticed that people are fairly interruptible while waiting, e.g. at bus stations or at parking lots. In contrast, they must not be disturbed at movie theaters, libraries or restaurants.

Author Keywords

Context Recognition; Location; Interruptibility; Smartphone Notifications

ACM Classification Keywords

J.4 [Social and Behavioral Sciences]

Introduction

Smartphones are an essential part of our everyday lives: they accompany us everywhere and are our personal, wearable computers. Besides their useful and helpful functionalities they might also bear an additional discomfort. An essential property of smartphones is that apps send notifications to inform the user. However, notifications happen to be disruptive and may interrupt users during their tasks [13]. This raises the need for an interruptibility-aware and smart notification management. Such a system has to be context-aware and analyze the situation of the user to be able to predict interruptibility. In addition, it might prioritize apps and promote important notifications or withhold notifications until a more opportune moment.

Smartphones are a small but mighty sensor system that can learn to automatically identify appropriate contexts. Previous research already shows that sensor measurements can be used to successfully build interruptibility models [2]. Smartphones grant access to different sensors and, thereby, context. Context is often associated with location [9]. First approaches already consider self-reported location as a feature for interruptibility [7, 11]. We want to go a step further by considering generic and automatically assessible locations. Thanks to Google's Places API[1] a vast amount of location information is easily accessible via GPS, including name of the location and its place type. However, this high number of places is difficult to handle and, most probably, not all of them are visited frequently and can be linked to interruptibility. In this paper, we present a reduction of place types followed by results of an online survey that assessed relations between such place types and self-reported interruptibility.

[1] https://developers.google.com/places/

Related Work

Related work already investigated when to interrupt smartphone users and if a context-aware system is able to recognize opportune moments to deliver notifications.

A very prominent example is *InterruptMe* by Pejovic et al. [7]. Their objective is to detect opportune moments to interrupt the user and deliver notifications. Among others, they take location into account. Their location features consist of descriptive location ("residential", "work","public") and location based on GPS as well as Bluetooth fingerprint and WiFi fingerprint changes. In our opinion, it is not enough to just differentiate between residential, work and public. More precise location types should be considered. Therefore, we investigate more detailed and generic locations as provided by the Google Places API.

Turner et al. investigate whether to push or delay a notification on smartphones [12]. They investigated correlations between interruptibility and contexts inferred from smartphone sensors. Their approach showed good preliminary results with accuracies up to 60%. However, they did not take location features into account which might have given even more insight.

Smith et al. test different machine learning techniques for interruption detection [10]. They let users react to incoming phone calls. Classifiers were trained on smartphone data which, however, did not contain location information. Their results are promising and show, basically, that the number of disruptive calls can be reduced. We assume that these results could be improved by additionally considering location like *InterruptMe* does.

Attelia, a middleware for notification management, detects breakpoints in a user's mobile interaction [6]. As a basis for breakpoint detection, they rely on system and runtime information of the operating system or the current application. The system was able to reduce user frustration by 28%. Though, the authors did not consider smartphone sensors in general nor location specifically.

Ho and Intille [1] investigated smartphone notifications and their impact on interruptibility. They argue that appropriate moments for interruption are changes in activity. Activity changes might relate to a user's location as high-level activities are often linked to a specific location, e.g. eating at a restaurant or exercising at the gym. This supports our idea.

Ter Hofte [11] analyzed interruptibility in relation to self-reported location, activity and a group indicator. However, self-reported location is difficult to generalize and might underly recall bias. Hence, we propose to use a common basis of place types and to assess them automatically.

The process of place identification was investigated in depth in a PhD thesis by Nurmi [5]. He defined his own place identification process consisting of data preparation, preprocessing, clustering and analysis in combination with a labeling process. However, this is a fairly complex process. We want to focus on an easy and straightforward solution using a generic API such as the Google Places API.

In summary, a lot of research focuses on interruptibility detection but rarely considers location as a feature. Approaches such as *InterruptMe* take location into account but on an abstract level and self-reported by the user. However, Google's Places API is able to provide place types based on GPS data in an opportunistic and fairly accurate manner. Considering this data is worth being investigated as it is easy to access and might contain useful insights.

Preliminary Considerations

Location Categories

To gain additional knowledge about places and to be able to have a more abstract taxonomy we decided to categorize the available places types. We reviewed related work to identify appropriate place categories.

Zheng et al. [14] propose to categorize places as *Food & Drinks*, *Sports & Exercises*, *Movies & Shows*, *Shopping*, and *Tourism & Amusement*. This categorization covers private contexts pretty well but lacks a business category.

Riboni and Bettini [8] rather focus on differentiating between private and business matters and propose *Communication / Meeting*, *Play*, and *Social Business Activity*. Liang et al. [3] propose a similar categorization and suggest *Work*, *Play*, *Develop*, and *Connect*. Liao et al. [4] include *Work* as well as *Sleep*, *Leisure*, *Visiting*, *Pickup*, and *On/Off Car*. However, these three categorizations are rather abstract and raw especially about private contexts.

In our opinion, Zheng et al. have the most representative selection as their categorization covers private contexts very nicely. However, they lack a business context. Therefore, we propose to include the category *Work and Education* to cover both business matters and education such as being at school or at the university. We also renamed the category *Tourism & Amusement* into *Recreation & Amusement* to include recreative activities.

Once place types are assigned to categories we can infer findings about the categories by analyzing the interruptibility of the place types within the category. In addition, this might allow an extension of an interruptibility detection system with new place types as a basic interruptibility at this place type can be derived from its category.

Place Type	Average
Movie Theater	1.42
Library	1.71
Restaurant	1.93
Gym	2.29
Café	2.67
Bar	2.78
University	2.81
Night Club	2.85
Clothing Store	3.23
Store	3.30
Shopping Mall	3.35
Grocery Store	3.40
Park	3.40
Post Office	3.51
Bakery	3.52
Bank	3.54
Meal Takeaway	3.55
Gas Station	3.71
Parking	3.91
Bus or Subway Station	4.01

Table 1: Average answer per place type stating if a user is rather interruptible (5) or not at all (1).

Place Type	Likelihood
Shopping	60.9 %
Work & Education	51.4 %
Food & Drink	48.9 %
Recreation & Amusement	44.2 %
Sports & Exercise	41.7 %
Movie & Shows	15.3 %

Table 2: Likelihood of being interruptible per place category.

Reduction of Place Types

The Google places API offers more than 120 place types[2]. It is likely that not all of these places are actually visited on a regular basis. To reduce the number of places recruited ten subjects which were picked randomly at the city center. Most of them are students which might be caused by the fact that campuses are located near to the city center. 60% of the participants are male, 40% female. We handed them a sheet of paper with all place types and ask them to cross out all locations that they visit less than once a month.

For all remaining place types we counted how many of the ten people did not cross them out. The selection criterion then was to keep all places that had a count of 4 or higher. This is a reasonable threshold, because it reduces the list by two thirds and with 0.95 confidence and 0.31 margin of error. That means that a majority of the represented population would visit this place regularly, with the error leaning towards keeping too many places instead of deleting too many. Eventually, the list was reduced to 20 place types:

- bakery
- bank
- bar
- bus / subway station
- café
- clothing store
- gas station
- grocery store
- gym
- library
- meal takeaway
- movie theater
- night club
- park
- parking
- post office
- restaurant
- shopping mall
- store
- university

These locations were used as a basis for the online survey.

[2]https://developers.google.com/places/supported_types

Assessment of Interruptibility per Place

We conducted an online survey to assess how disturbing notifications are depending on the location a person is in.

For each place type we asked:

- "In which category would you assign the currently displayed place type?" and offered one checkbox per identified category and allowed the participants to select multiple answers
- "At the displayed place type, how interruptive are smartphone notifications?" and offered a rating in form of a 5 point Likert scale ranging from "disturbing" (1) to "unproblematic" (5)

The categories were assessed to be able to abstract the interruptibility to higher-class places. The answers to the Likert scale can be interpreted numerically as a degree of interruptibility, i.e. 1 being "must not interrupt here" and 5 being "it is totally OK to interrupt here".

Participants

The survey was created on Google Forms and performed online. To recruit participants we spread the link to the survey via social media. 68 people answered the survey. They identified themselves as 50% male and 50% female. The average age was 33 years with a standard deviation of 12. Almost all participants had a school degree that qualified them for higher education. 63% even had a university degree. The largest occupational category was information and communication technology.

Results

The results of our survey are visualized in Table 1 and 2. It is visible that some places have a strong tendency towards "notifications are disturbing" or "notifications are unproblematic", respectively. The agreement to receive notifications at specific place types is shown by the results in Table 1.

Values near 1 represent that the users wish not be disturbed at this place type which applies to places such as movie theater, library, and restaurant. Values near 5 display that users do not mind interruptions at this place type which applies to bus or subway station and parking lots. There are several values around 3 which indicate that interruptibility at this place type is undecidable and highly user-dependent. Examples for these are university, night clubs and clothing stores. We assume that the interruptibility at these places might depend on the kind of interruption w.r.t. its origin (app) and social relation (involved contact person).

Breaking down interruptibility to place categories (cf. Table 2) reveals that no general decision can be made only based on the place category. We assume that further information such as activity or social activity would support the decision making. However, it is fairly obvious that users do not want to be disturbed at movies or shows.

Conclusion

Interruptibility might depend on the user's location as already investigated by *InterruptMe* [7] in form of self-reported locations. However, automatically assessed and generic location information might be more fruitful. As a preliminary investigation we ran an online survey to assess relations between place type detectable via the Google Places API and a subjective user ratings for interruptibility.

We noticed that people are fairly interruptible at bus stations or parking lots. This is reasonable as most people spent their time waiting and are not involved in a challenging task. Other place types at which users tend to be interruptible are gas stations and meal take-aways. Again, these are places in which the user is usually waiting for something, e.g. while the car is filled with gas or while the meal is prepared, allowing them to spend time on the smartphone.

In contrast, smartphone users must not be disturbed at the cinema or a library. This is also logical as these are places at which subjects are obliged to stay calm and keep quiet. Another "do not disturb" location are restaurants. We assume that this is due to the social nature of this place: users prefer to spend time chatting with friends or family or eating their food instead of being disturbed or distracted by the smartphone.

Many of these findings appear trivial and natural. However, it is a good sign that such place types are automatically detectable by smartphone APIs and do not have to be provided manually anymore.

These findings are a first basis for a location-aware interruptibility detection which might support a smart notification management. For interruptibility detection, further information such as activity and social activity as well as information about the notification itself (origin / app, social relation / sender) should be considered and investigated together with location.

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