Attelia: Sensing User's Attention Status on Smart Phones

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Abstract

In progressing ubiquitous computing where number of devices, applications and the web services are ever increasing, human user's attention is a new bottleneck in computing. This paper proposes Attelia, a novel middleware that senses user's attention status on user's smart phones in real-time, without any dedicated psycho-physiological sensors. To find better delivery timings of interruptive notifications from various applications and services to mobile users, Attelia detects breakpoint^[16] of user's activity on the smart phones, with our novel "Application as a Sensor" (AsaS) approach and machine learning technique. Our initial evaluation of Attelia shows it can detect breakpoints of users with accuracy of 80-90%.

Author Keywords

interruption; notification; user attention; mobile sensing; smart phones, machine learning

ACM Classification Keywords

H.3.4 [User profiles and alert services]: Systems and Software

Introduction

"Interruption" for users by notifications in multi-tasking environment has been a greater problem since amount of user's "attention" remains unchanged while amount of information provided has been increasing in emerging ubiquitous computing age.

The number of versatile networked devices, including user's carrying mobile devices, embedded sensors, or so-called "loT" devices have been ever increasing[9, 6]. Also the number of used applications, web services, and communication channels for users are increasing based on the technological advancement of rapid software/service development, deployment, and distribution.

Given such backgrounds, limited resource of **human attention** is the new bottleneck[7] in computing. From the view point of the human users, these excessive amount of provided information is often called "information overload" in a broad sense. Particularly in this research, we will focus on **interruption overload**, distraction for users caused by interruptions based on excessive amount and inappropriate delivery of notifications from computing systems.

Interruption Overload

The main cause of interruption overload for users is "notifications" from computing systems. Typical notification systems that deliver notification immediately make various negative affect to user's work productivity and even their emotion according to previous studies[1, 2, 5, 14, 8, 4].

Reflecting the recent trends in ubiquitous computing described in Introduction, there are also several distinctive characteristics observed in the recent notifications.

• Increasing diversity in types and sources of notifications: e.g., updates from friends over social network, query of participatory sensing[3],

- Multiple mobile devices of users as destinations: e.g., smart phone, tablet, or even wearable devices[9, 6].
- Wider range of urgency level: e.g., Early Earth Warning (EEW)[11] to which users need to physically react in a few seconds.
- All-day-long interruption situation: User's recent life style always with mobile devices makes interruption overload all day long.

Adaptive handling support of such notifications, including dynamic adaptation of notification timing, media, or content according to both current attention status of user and information to be notified, is clearly needed to ease user's interruption overload. Especially in the given situation, following are the distinctive requirements for such support.

- Feasibility in mobile devices: Users carry and use mobile devices, such as smart phones or tablets, as immediate devices for their task applications. Thus the system needs to fit the mobile platform, in terms of energy-efficiency, for example.
- **Real-time sensing:** Toward the adaptation on the fly, the sensing needs to be done in real-time.
- Applicability for diverse types of notification source: System needs to be applicable and easy to be deployed for diverse types of notification source.
- Affinity with all-day-long use: The sensing needs to be done all day long as long as the user's surrounding notification system is available.

Design of Attelia

Towards the realization of such adaptive notification support, we propose Attelia, a novel middleware that senses user's attention status on user's smart phones.



Figure 1: System Architecture of Attelia on Android Platform



Figure 2: Ground Truth Annotation with Attelia

Attelia detects **"breakpoint"** [16], a concept originally found in psychology field, as a temporal target in sensing appropriate timing for interruption. Breakpoint is a boundary between two adjacent actions that human's perceptual system can segment inside user's goal-directed activity. Related researches have shown that deferral of notifications until users' sensed breakpoints reduces interruption cost in terms of resumption lag and subjective frustration value[1, 13, 12]. Rather than sensing cognitive load with psycho-physiological sensors[10], we take an approach to sense coarse-grained but easy-to-measure indicator from which eventually appropriate timing for notification can be inferred, only with user's existing carrying devices.

As the concrete approach for breakpoint detection, Attelia introduces a novel **"Application as a Sensor" (AsaS) approach** where user's application usage pattern takes the role of sensor as well as the machine learning technique.

Using applications on smart phones as a sensors and running on the user's smart phone, Attelia achieves **affinity with mobile devices**. Using machine learning technique, Attelia achieves its **real-time sensing** capability. Being under the applications as middleware, and inputting UI events from the application currently manipulated, Attelia achieves its **applicability to diverse applications** and easy deployment, without any modification to the applications. Because Attelia does not need any dedicated sensors, such as psycho-physiological sensors, it fits nicely the all-day-long use case by users.

Attelia's System Architecture

Figure 1 shows the system architecture of Attelia implemented on the Android 4 platform. Attelia consists of an Android service including UIEventLogger,

BreakPointLogger, FeatureExtractor, and Weka[15] machine learning engine, as well as the GroundTruthAnnotator application, and off-line components for model training.

Attelia service is implemented as a "Service" inside the Android platform. Appropriately setting the permission of the service, without "rooting", it can input and log the stream of UI events, such as tapping, clicking, scrolling or modifications of UI components inside the currently-active Android application. Also, this implementation enables the service itself to be distributed through GooglePlay store and contributes to deployability of the system.

In the ground truth collection phase, ground truth of the breakpoint timings during application usage are collected via voluntary user's manual annotation. Figure 2 shows the screen shot with our Annotation application floating on the screen. While manipulating ordinary Android applications, the user pushes the floating button at the timing of their breakpoints. The Attelia service keeps recording the stream of UI events (excluding those from the annotation button) and breakpoint timestamps (timings that the annotation button was pushed) to the local storage. In the off-line model training phase, 45 defined features shown in Figure3, will be extracted for each time frame (three seconds duration) and will be input to Weka to train a classifier model. Finally in the testing phase, the UI event stream captured by the service will be input to the model in real-time on the mobile device, and the service detects breakpoints on the fly.

Evaluation

As our initial evaluation, we conducted a controlled user study among ten participants on six representative Android applications, and evaluated how accurately

Statistics on events'	Statistics on the
timing in the frame	status of the event
TimeGap_min	source UI components
TimeGap_mean	isEnabled_rate
TimeGap max	isChecked rate
TimeGap_stdev	isPassword_rate
Statistics on the location of the event source UI components source UI components with the source of the source source of the source of the Xieft, min Xieft, min Xieft, min Yielotom, m	Rate of accurrences of different UI const types TWFE_UVEV_UCLEXED_rate TWFE_UVEV_UCLEXED_rate TWFE_UVEV_UTLEXECTORS_Data TWFE_UVEV_UTLEXECTORS_DAta TWFE_UVEV_UTLEXECTORS_DAta TWFE_UVEV_UTLEXECTORS_DAta TWFE_UVEV_UTLEXECTORS_DATA TWFE_UVEV_UTLEXECTORS_DATA TWFE_UVEV_UTLEXECTORS_DATA TWFE_UVEV_UTLEXECTORS_DATA TWFE_UVEVUE_UTLEXECTORS_DATA TWFE_UVEVUE_UTLEXECTORS_DATA TWFE_UVEVUE_UTLEXECTORS_DATA TWFE_UVEVUE_UTLEXECTORS_DATA TWFE_UVEVUE_UTLEXECTORS_DATA TWFE_UVEVUE_UTLEXECTORS_DATA TWFE_UVEVUE_UTLEXECTORS_DATA TWFE_UVEVUEUEUEUUTLEXECTORS_DATA TWFE_UVEVUEUEUEUUTLEXECTORS_DATA TWFE_UVEVUEUEUEUUTLEXECTORS_DATA TWFE_UVEVUEUEUEUUTLEXECTORS_DATA TWFE_UVEVUEUEUUTLEXECTORS_DATA TWFE_UVEVUEUEUUTLEXECTORS_DATA TWFE_UVEVUEUEUUTLEXECTORS_DATA TWFE_UVEVUEUEUUTLEXECTORS_DATA TWFE_UVEVUEUEUUTLEXECTORS_DATA TWFE_UVEVUEUEUUTLEXECTORS_DATA TWFE_UVEUEU

Figure 3: Features used in Attelia



Figure 4: Cross-validation result with J48

95	
90	
2 85	
5 80 ·	
Accuracy 12	Twitter
5 70	-Yahoo! News
jų j	Browser
ass	—Gmail
° 60	-Kindle
55	-YouTube
	All Apps Unified
50	
	0.5 1 1.5 2 2.5 3 3.5 4 4.5 5
	Frame Length (seconds)

Figure 5: Cross-validation result with RandomForest

Attelia can detect breakpoints. The participants were university workers, students, and staffs with at least intermediate knowledge on the Android smart phones. The applications were (1)Twitter, (2)Yahoo! news, (3)Browser, (4)Gmail, (5)Kindle, and (6)YouTube. For each application, each participant was asked to manipulate it "naturally as usual" on Galaxy Nexus with our system for five minutes, and asked to annotate breakpoints according to their own subjective sense.

Figure 4 shows the accuracy results from 50 fold cross-validation with the models based on C4.5 decision tree (J48), while Figure 5 shows the results with RandomForest. The models were created for each of six applications, with different frame length configurations from 0.25 seconds to 5 seconds. In both cases, with frame lengths of 2–3 seconds, accuracy values are above 80–90%. We also tried to make a unified model based on the ground truth of all six applications. Although we need further evaluation and analysis with more applications, the current unified model shows the accuracy around 80–85% which brings us quite positive insight.

Conclusion

This paper proposed Attelia, a novel middleware that senses user's attention status on user's smart phones, in real-time, without any dedicated psycho-physiological sensors. Attelia detects breakpoint[16] of user's activity on smart phones, with our novel "Application as a Sensor" (AsaS) approach and machine learning technique. Our initial evaluation showed quite optimistic accuracy around 80–90%.

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