Capturing mobile experiences: Context- and time-triggered in-situ questionnaires on a smartphone

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Introduction

Measuring the behaviour and experience of people unobtrusively in different context situations is desirable in order to achieve more valuable results. Questionnaires applied directly in the situation of interest have the advantage that memory effects are prevented, which are a common issue with retrospective measures [1]. However, they also interrupt the ongoing interactive experience. To be able to collect feedback directly in a targeted context situation either requires direct context interviews by a researcher, or the use of mobile devices that the study subject can use in the situation. Context interviews are a reliable in-situ measurement method; but they require a study facilitator to accompany each participant during the trial and therefore are very resource and cost intensive. Mobile devices like smartphones are very useful platforms for in-situ questionnaires, as they allow for an unobtrusive interaction with the user on a day-to-day device [2]. It also allows an easier access to the data for the researchers [2], in contrast to inputting the data from paper questionnaires. However, due to the non-presence of a human observer there is a need to create mechanisms that control the triggering of the questions. Different approaches to solve this problem have been proposed and implemented. Questionnaires can be triggered randomly without knowledge of the context situation (traditional experience sampling), or available data on context (e.g. location, availability of wifi, etc.) can be used (triggered ESM).

In this paper we present a new tool for in-situ questionnaires delivered on a mobile device, which implements the idea of being able to react to the imminent context of people and provides an advanced approach to answering questionnaires in-situ. We also describe the insights we gathered from a qualitative user study with 18 participants and point out the challenges we faced.

Related Work

Intille et al [4] described and developed a tool for context aware experience sampling. The tool uses context-aware sensors to collect feedback from the user only in certain situations, and according to them triggering the questions based on context-awareness helps minimize the interruption annoyance of the ESM. This general idea was further developed by different researchers. Micallef et al. [3] aimed for identifying the most interesting temporal slot to ask questions in a 'ground truth' data collection. To find the optimal moment, they detect if a user was either doing a physical activity (by using accelerometers) or was at a certain location (by using Wi-Fi access points). "MyExperience" [5] is an open source system that captures in situ data on mobile phones and portable devices. It captures device usage data, such as number of phone calls, SMS, used applications and media captured, and phone data, like GPS and Bluetooth and calendar information. This information is used for user experience sampling. Lathia et al. [7] developed an open source smartphone library for computational social science. Similar to our approach they used raw sensor data for triggering experience sample questions. Recent research has also found that the selection of trigger sensors and stimuli has an important influence on the data, and that more elaborated methods for defining trigger situations e.g. by combining multiple sensors are desirable in order to increase the quality of the measurement [8].

Design of the In-Situ Tool

In our work we are addressing this problem by developing a modular framework that allows combining and analysing different sources of context information. In our framework we consider different sources of context information: (a) Sensor data that relies directly on the context - lighting conditions, noise conditions, humidity, temperature, etc.; (b) Sensor data that relies on the persons behaviour in this context - heart rate, speed of movement, eye-tracking data etc.; (c) Location information - GPS data, available Wi-Fi access points, cellular signal strength, etc.; (d) device usage data in the context – number of Bluetooth devices arround, number of reveived calls, number of received messages etc. Besides multiple sources of data there is also a wide range of possibilities to react to the context depending on the goal of the study. Typical reactions in research activities are prompting a questionnaire to the user, triggering experience samples, storing the device state, etc. To enable this wide range of possibilities we designed a middleware that receives messages from the context measurement sources, reacts to this message by computing rules and trigger appropriate reaction. This approach is supported by modern software architecture principles. For example the Android operating system relies on (so called) Intents [1] [10] that are used for communication between different user interface screens, but also different applications. Using this message based approach it is possible to combine different modules (e.g. off the shelf applications) to a more complex system. As a proof of concept we developed a context aware experience sampling prototype that follows this modular approach. Basically the system consist of three modules: (1) a framework for measuring context, to be more precise the sensor values of a smartphone (2) a rule engine that reacts to the sensor values and subsequently triggers the desired question (3) a questionnaire app to provide different questions to the user. An overview of the prototypes architecture can be found in Figure 1.

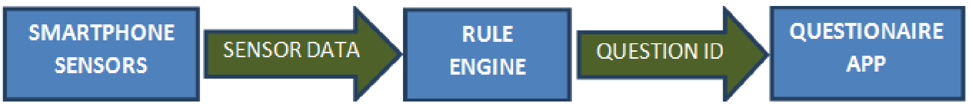

Figure 1. Overview of the approach and the used applications.

Smartphone - Sensors. To measure context information, in our proof-of-concept application we use the built in sensors of an off the shelf smartphone (Samsung Galaxy S4) and additionally an off the shelf heart rate monitor (Zephyr HRM BT). The sensor values were captured using the application AIRS [6]. This app measures selected sensors and subsequently sends intents to our middleware as soon as the sensor value changes. To allow realistic measurement of context parameters (e.g. light or sound) the smartphone was strapped to the user's non-dominant hand – see Figure 2. Also, this placement supports the utilization of the smartphone as input device.

Rule Engine. We developed a middleware that allows the researcher to define rules and thresholds for the sensor measurements which need to be reached, in order to show the user the appropriate questions. The middleware can deal with different rules. Basically there are six types of rules:(1) higher ($x >$ threshold), (2) lower ($x <$ threshold), equals ($x=$threshold), (4) is not (x != threshold). (5) increase ($\Delta x>$ threshold) (6) decrease ($\Delta x>$ threshold). Basic rules can be combined into more complex rules (e.g. if light > 10lumen and noise <100 decibel). Moreover time related thresholds are possible as well (e.g. if noise is higher than 90db for 3 minutes). Additionally it is also possible to set time related mean thresholds (e.g. on average noise is higher than 90db for 3minutes). For our proof of concept implementation a simple approach was chosen. The researcher defines the rules by hand in an XML file which is stored on the device – see Figure 3. Using this approach it is possible to build complex rules that allow detection of complex semantic contexts.

Questionnaire App: The questionnaire app is based on an in-situ data collection tool called Tempest [9] and provides the question to the user after receiving an intent with the question ID from the middleware. It provides different types of questions to the user, e.g. multiple choice questions, free text input, selection grid, etc.

[1] Intent - http://developer.android.com/reference/android/content/Intent.html - Accessed 8. July 2014.

Additionally questions can be combined into a series, which can be triggered by a single intent. All questions are shown and answered on the smartphone.

Figure 2. Smartphone attached to the participants non dominant hand.

```
<CombinedRule>//Type of Rule either CombinedRule or CombinedTimerRule
   <Runs>5</Runs>//How often this rule can be fired
   <QuestionID>QLi1</QuestionID>//Question ID triggered in the questionnaire app
   <BasicRule>
         <ID>ID_MORE</ID>//defines the type of rule - higher, lower, equals, etc.
         <Sensor>com.airs.sensor.LI</Sensor>//the sensor – in this case light
         <Threshold>100</Threshold>// if values is more than threshold
   </BasicRule> // end of first basic rule
</CombinedRule>
```

Figure 3. XML Example - CombinedRule, that consists of one BasicRule. The rule fires if the light sensor is above 100 lumen.

User Study

The goal of the study was to evaluate the practicability of our approach in real conditions and to study the appropriateness of the context detection. Moreover to receive feedback on the perception and opinions of users regarding the context aware questionaire, we compared this approach with time triggered questionaires and retrospective questions. We defined three different context situations a person encounters during a shopping trip in a shopping mall, that are suitable points for measuring user experience: (1) Outside of the building (to measure the experience before/after the overall shopping trip) (2) inside the building (to measure the experience before/after shopping), (3) inside a shop (to measure the experience while actually shopping).

18 participants (nine women) were asked to perform a series of tasks inside two different shops in a shopping mall. The tasks were put in an order that participants passed all three defined situations (outdoor, inside the building, inside a shop). We used a between-subject design with three groups (each consisting of 6 participants). A question triggering approach based on pre-defined time intervals was used for the first group. The second group received questions triggered by the context-aware system. A third group was asked to fill in the questions at the end of the trial, in a retrospective manner (in contrast to the two other groups which answered the questions in-situ as soon as they were triggered). All groups answered the questions on the smartphone. The questions were related to the tasks and featured closed and open-ended questions. After the trial the participants were asked to describe their experience with the used method in a concluding interview.

For the context recognition – based on two pre-studies – we defined the following rules: (1) In shop: Movement speed lower 0.3 km/h, temperature higher 15 degree Celsius and Noise below 70 decibel (2) Indoor: Movement speed between 0.4 and 0.9 km/h, temperature higher 15 degree Celsius and Noise above 65 decibel (3) Outdoors: Movement speed higher 0.8 km/h, temperature lower than 10 degree Celsius (study was conducted in winter).

Results and Discussion

Performance measurements: Within the six participants using the context-recognition setup, there were a total of 42 questionnaire items that were triggered. 37 were triggered correctly, 2 items were triggered in the false context and 3 items were not triggered at all - because the context was not recognized correctly by our system. While the different items were supposed to appear only once during the specific context, and also never twice in a row, there were certain cases were these requirements were not met. E.g. a fast walking speed but long task completion time resulted in the appearance of three questions items in one shop. There was also a problem with the temperature sensor, as it takes a long time to adapt to fast changing temperatures. In the time-triggered group of 42 total questionnaire items triggered, 23 were triggered correctly, 4 only narrowly false and 15 false. The first outdoor questionnaire items were always asked in the correct context. In contrast the first indoor questions afterwards always triggered too early. The question items for inside a shop were triggered false only two times.

User Experience: Participants of all three groups were asked about their experience with filling out questionnaires on a smartphone. The majority of the 18 participants were pleased with answering the questions on the smartphone, though one third said that different input method (especially bigger in size) would have been more helpful. The two groups answering questions in-situ (time triggered and context triggered) said that they felt not distracted by the questions. Participants preferred multiple-choice questions, due to their easiness, but also answering speed. About one third of the participants said that the right answering format is dependent on the situation, as sometimes more detailed and expressive answers are necessary.

13 out of 18 participants felt uncomfortable about carrying the smartphone on their wrist – mainly due to being afraid that it might fall down. More than half of the participants preferred the smartphone to answers on paper. Participants argued that using the smartphone is quicker and more convenient than paper questionnaires. When asked if the questions came at the relevant moment, participants in the context-recognition group said the questions had perfect timing, with the exception of two participants. In the time triggered group, participants had mixed feelings regarding the timing. Some participants perceived that questions were triggered at the right time, even though they arrived too late. The retrospective group was asked, if the questions should have been asked during or right after the task. Participants stated that the short amount of time didn't result in recall difficulties of their opinions and thoughts on the tasks. Although participants hypothesised that if the study duration would have been longer it would have been more accurate in the situation.

Conclusion

In this paper we developed a framework for context aware questionnaires, developed a proof of concept and conducted a first user study. Our work shows that even with a simple rule engine it is possible to react to the user's context accurately. A limitation of our approach is that the rules need to be defined and adapted by hand, which can be tedious. In future work we plan to extend our framework by developing an advanced, intelligent middleware that uses machine learning principles to detect and define appropriate contexts automatically.

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