Identification of Relevant Sensor Sources for Context-Aware ESM Apps in Ambulatory Assessment

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Abstract
The experience sampling method (ESM) is applied in ambulatory assessment to prompt subject self-reporting. Existing mobile apps provide time-triggered prompts but lack event-triggers. Hence, the sampling might not occur in moments that are of interest for a psychologist. To identify relevant sensor sources and contexts we conducted an online survey with ambulatory assessment experts. Most relevant for these experts are time, date and user activity, followed by location, notifications and accelerometer. A feasibility test proved that all relevant sources are accessible on Android phones. We also assessed the desired granularity of the data gathered from each sensor source. Our results are a first step towards an ESM platform to create context-aware Android apps for ambulatory assessment.

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Mobile Sensing; Context Awareness; Experience Sampling; Ambulatory Assessment

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Introduction
Assessing subject information in everyday life during everyday activities is an emerging task [4].
Especially when handling depressive patients or patients with personality disorders it is important to keep track of their emotional state [3]. A momentary assessment is required. This is where ambulatory assessment comes into play [2]. Using experience sampling methods (ESM), subjects are provided with questionnaires and self-report prompts to report their current situation. Several challenges arise.

On the user side, the reporting (1) has to be made quick and easy and (2) shall not interfere with the everyday activities too much and should be easily integrable into everyday life. That means that the numbers of questions and prompts has to be kept to a minimum.

On the expert side, subjects shall (1) provide self-reports in relevant situations – which are hard to grasp – and (2) provide relevant information about their contexts continuously. That means, that prompts has to be triggered in relevant situations and that the device has to automatically and continuously log user information.

We propose to address those challenges by leveraging smartphone sensors and context recognition methods.

So far, ESM apps primarily only considered accelerometer and location data [6]. To generally identify the sensor sources that are relevant for experts in the field of ambulatory assessment, we interviewed experts and provided an online survey.

Related Work

The experience sampling method (ESM) is applied in ambulatory assessment for several years now. There exist platforms\(^1\,^2\) allowing non-programmers to create their own ESM app that, in addition to providing experience sampling questionnaires, gathers context information from sensors. We will focus on those that include a preliminary version of event-triggers in addition to time-triggers.

One of them is Ohmage\(^3\). It allows time- and location-triggered prompting of self-reports. In addition, it collects sensor data from accelerometer, wifi, mobile radio cell and GPS. They allow users to adjust the event-triggers to enhance compliance. Though we prefer to give those privilidges to the experts.

Another platform is MyExperience\(^4\). Experts can design ESM studies by choosing from a set of question types and by selecting sensors to be accessed, e.g. GPS, GSM or keystroke dynamics. In addition, experts can define event-triggers based on additional, external sensors e.g. self-reporting triggered by an increase of heart rate. The studies are then runnable on Windows Mobile devices.

The Android equivalent to MyExperience is movisensXS\(^5\). It offers a similar functionality as MyExperience, but in addition offers additional wearable sensors. So far, they only consider a level of activity, measured by their activity sensor, and GPS locations as triggers.

We want to investigate additional sensor sources and contexts that are relevant for non-programmers and ESM experts – especially in the area of ambulatory assessment. The findings shall serve as a basis for a platform that enables building such context-aware ESM apps.

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\(^1\)http://beepme.yourexp.at
\(^2\)http://www.cl.cam.ac.uk/~nkl25/easym/
\(^3\)http://http://ohmage.org/
\(^4\)http://myexperience.sourceforge.net/
\(^5\)https://xs.movisens.com/
Context Survey

We created a survey \(^6\) that gathered the opinions of ambulatory assessment experts regarding relevant sensor sources and context. The survey consisted of 20 questions concerning the relevance of sensor sources and the desired granularity in which data is to be gathered. We applied the MoSCoW priorization \(^1\), i.e. asked the subjects to state which sensors are “must”, “should”, “could” or “won’t”. In addition, we added ”don’t” to express an exclusion of a sensor (similar to a “must not” \(^7\)).

The survey was handed out to members of the Society of Ambulatory Assessment. Twenty of them answered the survey.

We ranked they answers from 0 (“don’t”) to 4 (“must”) and averaged the values for each sensor. Table 1 visualizes the results and a priorization highlighted by colors.

The currently most relevant sensor sources are time, date and user activity. Though, location, notifications and accelerometer data is also of interest.

We also asked for the desired granularity of data from specific sensors. The experts were free to choose multiple options as a combination of different granularities might be of interest for them. Table 2 presents the answers and how often the answer was picked.

Many experts are interested in having either specific knowledge about the user context (e.g. specific time or certain day) or an abstraction of it (e.g. abstract location).

Though, for all events, experts have to consider in which amount they want to trigger prompts by those events as several of the contexts might occur very often (e.g. “receiving an SMS” or “receiving a notification from WhatsApp”).

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\(^6\)http://goo.gl/forms/M0bdcx4swy
\(^7\)https://www.ietf.org/rfc/rfc2119.txt

<table>
<thead>
<tr>
<th>Sensor Source</th>
<th>Granularity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>Specific time (21); range (4); daytime (3)</td>
</tr>
<tr>
<td>Date</td>
<td>Certain day (21); repeating day (6); higher contexts (5); range (4)</td>
</tr>
<tr>
<td>Location</td>
<td>Abstract location (17); certain location (14); certain area (5)</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>Movement yes/no (15); averaged movement (14); movement in certain axis (11)</td>
</tr>
<tr>
<td>Notifications</td>
<td>Any notification (10); notifications from a certain app (8); number of notifications (7)</td>
</tr>
<tr>
<td>Ambient light</td>
<td>Light level range (12); Specific light level (7)</td>
</tr>
<tr>
<td>Ambient noise</td>
<td>Speech recognition (10); noise level range (10); specific noise level (8)</td>
</tr>
<tr>
<td>Calendar</td>
<td>Calendar status (10); number of events (8); priority of events (3); calendar type (1)</td>
</tr>
<tr>
<td>Weather</td>
<td>Weather context (16); temperature (15)</td>
</tr>
<tr>
<td>Bluetooth</td>
<td>Device identification (10); number of devices nearby (8)</td>
</tr>
<tr>
<td>App-Activity</td>
<td>Certain app (9); certain category of apps (7); number of active apps (2)</td>
</tr>
<tr>
<td>SMS/Telephone</td>
<td>Any SMS/call (12); SMS/call from a certain number (7); number of missed calls/SMS (7)</td>
</tr>
<tr>
<td>Social networks</td>
<td>Number of posts (8); activity (8); number of friends (6)</td>
</tr>
</tbody>
</table>

Table 1: Priorization of sensors. Ranging from “must” (≥ 3), over “should” (≥ 2), to “could” (≥ 1.0).

Table 2: Overview of the answers wrt. the desired granularity of sensor measurements. The number in brackets indicates how often the answer was picked.
Feasability Test
In a next step, we evaluated which sensor sources are accessible and deliver useful results. Therefore, we implemented the sensors using Android 4.4.4 KitKat. We were able to implement most of the sensors shown in Table 1. Unfortunately, current app, app crashes and touch activity are only accessible with root access and hence cannot be accessed on the subjects’ own phones. Those sources are only available on test devices that are handed out to the subjects by the study lead.

Conclusion
Smartphones are a ubiquitous, wearable sampling system that can be used for ambulatory assessment [5]. So far, accelerometer and location data were primarily for event-triggers. We conducted an online survey to gather sensor sources and contexts that are relevant for members of the society of ambulatory assessment.

Most relevant for them are time, date and user activity... Though, location, notifications and accelerometer data is also of interest. We also assessed the desired granularity for the measurements of each sensor source. A feasibility test showed that in principle all sensor sources are assessible, though some only with root priviliges. That means that smartphones contain a number of highly relevant data sources that are not yet actively accessed and used for ambulatory assessment.

We intend on implementing an ESM platform for ambulatory assessment experts to design their own context-aware ESM apps by allowing (1) to continuously gather data from the identified sensor sources and (2) to define event-triggers for prompts based on context information. In addition, an automatic feature selection should pick the most effective sensor sources per subject.

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References