Reading the tea-leaves in an intelligent Coffee Corner: understanding behavior by using sensory data

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Abstract

This article discusses the challenges for methodological innovation based on experiences in an experimental "Living Lab" setting; an interactive and context-aware coffee corner in a research institute where people that take coffee can use a variety of services offered by intelligent environment at the coffee corner's site. It also collects sensory information of users while they are moving along the institute and when they interact with the coffee corner. The analysis of contextual data allows the construction of a behavioral model of users in a non-intrusive manner. We explain how this method can be used to get insight in measuring behavior in context in an unobtrusive way.

Keywords

Living Lab, Context-Awareness, Behavioral Models, sensory data

Introduction

Human-centered design is nowadays a common practice and many methods and tools are at hand to this scope. However, we still see many projects that face difficulties in designing intelligent systems that meet (future) users' needs. The reason might be emerging technology itself, because we face more complexity in designing intelligent environments. Nevertheless, the exploitation of such environments enables researchers to come close to the users and to understand their expectation when using those environments.

A Living Lab exploits intelligent infrastructures for measurement purposes instruments, moves research out of laboratories into real-life contexts, and provides opportunities to non-intrusively study social phenomena in users' social and dynamic context of daily life. The Living Lab concept has been acknowledged in Europe as an open innovation instrument that is appropriate to study questions related to human behavior and experiences; involving areas of user interface design and ergonomics as well as user acceptance, extending to user co-design process, and it leads to service or product creation [9]. It might be clear that the Living Lab concept opens a wealth of possibilities to exploit the evaluation of intelligent environment. However, according to Mulder and Kort [7] "many of the automated tools alone do not deliver the desired insight; they need to be combined with common methods such as interviews and focus groups which either provide input for the automated measurements (which things should be captured and asked for during experience sampling) or provide additional information after the automated measurements (clarifications of specific experience sampling data, behaviors or contexts in which it appeared)".

Differently stated, there is still a need for research in methodological guidelines and tool requirements for data-analysis. In particular, analysis techniques are required for correlating objective behavior and subjective user experience data into relevant design context parameters.

In the remainder of this article, we describe an experimental Living Lab setting to get insight in measuring behavior in context and in an unobtrusive way. Using a context-management framework infrastructure, we are able to collect, store, and analyze a great amount of contextual data. The analysis of contextual data allows the construction of a behavioral model of users in a non-intrusive manner. Starting from this experimental setting, issues for data collection and analyses are discussed, as well as the current availability of methods and tools for building and exploiting user behavioral and experience models are reviewed in general Living Lab' scenarios.

The Intelligent Coffee Corner

The intelligent Coffee Corner is a real-life coffee space with reasoning capabilities and intelligent services located throughout a research institute, which employs about a hundred workers situated in two connected buildings. Each building has four floors. Moreover, the employees that work in different projects are spread (rather randomly) across different office locations. Every floor has a coffee space and is equipped with a high density of sensors allowing for device discovery and human detection by using Bluetooth dongles, RFID readers, WLAN access points, video cameras, pressure mats, computers, and advanced displays (Figure 1).

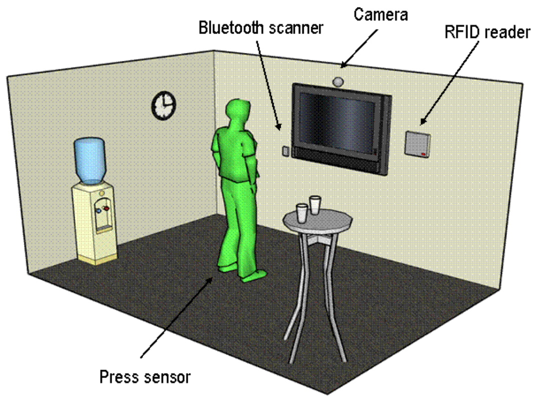

Figure 1. *The intelligent Coffee Corner, equipped with sensors such as Bluetooth dongles, RFID readers, WLAN access points, video cameras, pressure mats, computers, and advanced displays.*

Most employees carry detectable devices (e.g., Bluetooth-enabled mobile phones or PDAs and WLAN-enabled laptops) with them. In addition, all employees wear by default a RFID-enabled badge, which is needed to open doors in order to access the different floors in the building. These badges are also used to sense employee locations throughout the institute. Similar to the Living Lab concept, our intelligent Coffee Corner finds success if people and technology continually interact [8].

Coffee break brainstorming, questionnaires, surveys, scenarios, contextual inquiries, participatory design, focus groups, paper prototypes, in depth interviews, and technology probes are some of the traditional tools that have been used so far to gather user needs, expectations, perspectives, ideas, feedback, or inspiration during users' daily activities [2]. While most of these tools engage users' involvement in an explicit way, our intelligent Coffee Corner also provides tools to get information from users and insight in their behavior in an implicit and less obtrusive manner. Examples of this implicit way of data collection that uses the capabilities of intelligent environments are listed in the following:Logging: information about the use of application, which and how frequently.

Sensing: information about the (physical or virtual) context of the user.

User-generated content: information that users have created on their own initiative; thus for other reasons than research might have intended.

Sensing of contextual information

For obtaining information about users' behavior and users' experience we make use of an infrastructure that enables the collection and management of heterogeneous context information obtained from various heterogeneous sensors. Such an infrastructure is called Context Management Framework (CMF) whose design is described in [10].

The CMF is a highly distributed service infrastructure that enables context-sensitive applications to discover and obtain context information. Examples of context information supplied by the CMF include GPS location coordinates, WLAN access point associations, RFID reader data, Bluetooth scan data, desktop keyboard typing status, presence information, and Outlook calendar meetings. In an implicit way, the CMF collects raw data from these context sources, processes the data by fusion and reasoning to infer higher-level context information and/or better quality context information so that it is useful for a service provisioning that meets user requirements. Inference in the CMF is done with various reasoning components that fuse and enrich sensed information to higher semantic levels. Each reasoning component can use its own internal algorithm and inference mechanism.

To have a shared understanding of the meaning of the information that is delivered and exchanged by the CMF, the sources of information exchange their information as instances of a shared ontology. The (extensible) ontology describes both the types of context information as well as the relations between these types. An overlay framework takes care of aggregating context information per entity. It does so by using specialized broker components that, in addition, are able to enforce policy rules. This allows users for instance to specify who may access their privacy-sensitive context data [3].

In summary, thanks to this CMF we are able to collect, store, and analyze a great amount of contextual data and opens possibilities for advanced study of user experience and user behavior. The CMF has proven to be a robust and flexible underlying infrastructure for several mobile health and office applications. One such example is the "Colleague Radar" application, a location-tracking service with context-aware security and privacy features. The "Colleague Radar" enables access to context of colleagues, among which, their location inside or outside the office. A screen shot of the application user interface (as it runs in the Coffee Corner) is shown in Figure 2.

The Colleague Radar application is an example of presence-aware services whose benefit from an intelligent management of context-information is high. Its identification and authentication mechanism is designed to be dependent on contextual information. User authentication is done in a very user friendly manner based on the locations of different user identity tokens such as an RFID employee card or Bluetooth phone, that the user is assumed to carry with him/her [4]. This is supplemented with face recognition to improve user identification and authentication even more [5].

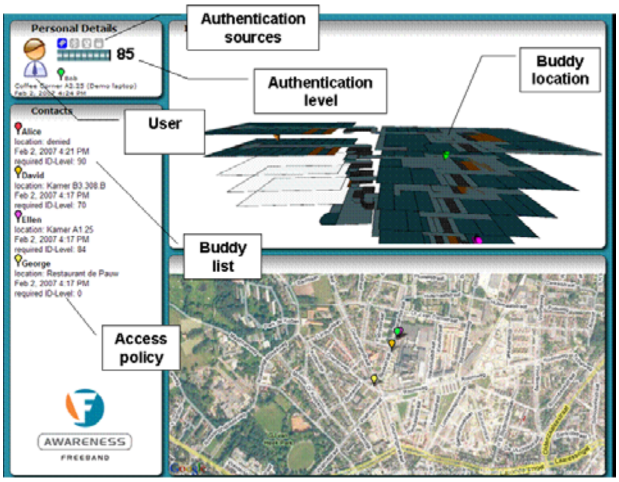

Figure 2. *A screen shot of the Colleague Radar application. The up-left panel shows the ID-level of the user and the devices that have been used in the identification process. The down-left panel is the list of colleagues that have agreed to have their position shown considering the user's identity and current ID-level. The two right panels show, graphically, the position of the colleagues in the building, and in the area around.*

The availability of advance type of contextual data, such as behavioral models tailored per user, would help in improved user identification and authentication procedures (users can be recognize thanks to their behavioral patterns) whose reliability is a key quality for the success of this kind of application.

Sensory data for measuring behavior

The high density of sensors and intelligent devices, managed through the CMF, enable not only to support device discovery and human detection and identification, but also to observe user behavior based on the sensed information. In this section we discuss the challenges for methodological innovation in understanding user behavior and user experience in context.

Context information, when aggregated in time, can potentially be used to determine behavioral models of users and, consequently, to improve the provisioning of customized services. One general methodology consists of processing raw data that originates from context sources and to obtain higher quality context information. For example, probabilistic methods can be applied to positional raw data to evaluate the expectation we have in a person's position. This measure can be useful to build for instance automatic authentication or authorization of users depending on the location of their identity tokens. When this information is combined with other kinds of contextual data, for example location or activity information obtained from Outlook agenda, even more accurate reasoning can be done; for example the use of a plotter can be allowed in a certain meeting room only when the user is actually in the room and attending to a meeting.

The collection and the organization of raw contextual data into an event structure (e.g., a temporal timeline) allow for the understanding of advanced situational events. By using model checking algorithms for temporal logics (cf. [1]) it is possible to check properties that express user behavior in specific situations, like for example, "might the user have forgotten the meeting?". Such an event, in fact, can be translated into temporal expressions like "the user has the meeting in his Outlook agenda, which he usually synchronizes with his mobile phone and he is actually in the library". The recognition of contextual and temporal situations fosters the design of better and innovative services. In the previous example, the missing user could be automatically alerted of the meeting on his mobile phone (despite the fact that his local agenda is not updated); if he has forgotten the device somewhere, a close colleague can be contacted instead.

The evaluation of temporal events can be either momentary (e.g., where he is now), or can be used reconstructive (e.g., where he has been) or anticipative (e.g., where he is likely to go). This last aspect is related to prediction of events, which is quite difficult but still possible. Statistical model, constructed from existing sensory data, can be utilized to predict a person's indoor location at a specific point in time. Data mining techniques based on machine learning methods (e.g., Bayesian Networks, neural networks, decision trees) and plan recognition techniques are available. Reasoning on (not strictly temporal) context information aims to improve the prediction. Bluetooth dongles and desktop activity as well as Outlook Calendar information can be used to determine and predict the user's movements.

The analysis of context information allows also an unobtrusive identification. When a user is trying to access a resource, his identity is estimated by processing the contextual information gathered so far, for example by processing the position of the devices that are expected to be carried by the authenticating identity. Automatic identification can be particularly useful when privacy is also requested to be preserved. First, contextual information can be preferred to other confidential identity token like passwords or PINs (the intelligent Coffee Corner, for example, is a public space potentially insecure to eavesdropping). Then the single contextual pieces of information remain related to anonymous (distinct) entities until an identification request is forwarded; in that moment, the system is allowed to calculate which identity is mostly believed trying to log in.

The use of contextual information allows also reasoning about the trustworthiness of certain actions. Inconsistencies in the event structure might be witnesses of untrustworthy situations. For example, a user mobile that is moving in a different direction from a user badge may mean that the user's phone has been stolen. In a city-wide scenario, a user withdrawing money from closer but different cash dispensers in a very short time (when the user is expected to be at work) may identify a debit card robbery. Temporal properties satisfiability could be enhanced with quantitative methods for trust evaluation; critical situation being labeled with a value indicating the level of criticality which is obtained by considering also past experiences or even recommendations.

Discusssion and conclusions

The analysis of contextual data for the inference of users behavior or movement patters is affected by a number of issues that any Living Lab must carefully take into account. Hereto, the following issues are critical:

Reliability and availability of context info. Are contextual data always reliable? What is some information is not available when needed?

Fusing different heterogeneous context sources: How to map patterns for each source to each other? How to fuse non-homogeneous data (e.g., a pattern in a location-database with one in a temperature database to derive someone is being ill or is running?)

Triggers for behavior. What does trigger a user to behave in a certain manner?

Effectiveness of sensory data for user behavior modeling: How much does the derived user behavior model match the real behavior? How does the fitness of a behavior model relate to the set of sensors used and their quality of context?

Data reliability is a first prerequisite for answering research questions. In observational research, reliability of data refers to the degree of agreement between sets of data collected independently from the same scene by two different sensors or by the same sensor at different times in the data collection process. Various quantitative measures have been used by researchers for the assessment of the degree of agreement between sensors or observers. Jansen, Wiertz, Meyer and Noldus [6] discuss several methodological problems related to the assessment of observer agreement on observational data, how these can be solved, and how these solutions have been implemented?

Besides human behavior, the characteristics of unobtrusively observing a person in a real-world environment should be taken into account. Some physical or virtual phenomena are difficult or impractical to observe due to the availability, cost or obtrusiveness of the required sensor. Observations may be missed due to sensor hardware failures, connectivity problems or the user moving outside the coverage range of a sensor. In addition, the quality of an observation depends on the characteristics of the sensor, such as its accuracy and sensitivity. Finally, observations of different phenomena are often related. In the reasoning process, the qualities of each observation as well as relationships between observations thus need to be taken into account.

Typical approaches for determining user behavior assume the availability of actions or derive actions from sensor data in a single step. In contrast, we argue that inferring actions from sensor data in multiple steps is more effective. This multi-step approach allows for specialized reasoning techniques to tackle specific parts of the inference process. At various abstraction levels, contradictions and superfluities can be eliminated and missing observations can be compensated by combining and interpreting contextual information. This process results in a gradual reduction of the observation space while enriching the context information. The multi-step processing of sensor data into actions and enriched context information is facilitated by the described CMF.

The availability of context information gathered from multiple sensor sources provided unprecedented opportunities to study user behavior and experience in a non-intrusive, natural manner. Finally, we are able to study the impact of innovative and intelligent solutions in a naturally way that is not intrusive for users. However, a lot of work needs to be done in the area of context reasoning and behavior assessment.

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