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Reading the tea leaves in an intelligent Coffee Corner: Challenges for understanding behavior

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This article discusses the challenges for methodological innovation on the basis of experiences in an experimental Living Lab setting: a context-aware Coffee Corner in a research institute. A context-aware infrastructure collects sensory information on users while they move and interact. People getting coffee can use a variety of services offered in the intelligent environment at the Coffee Corner's site; for example, a colleague-radar application allows users to see the current positions of their colleagues in the building. At the same time, it identifies and authenticates users using proximity-aware and context-aware security features. Apart from proximity and context awareness, the analysis of contextual data allows the construction of a behavioral model of users that can be used to customize the services offered at the Coffee Corner. We explain how the Living Lab allows us to measure behavior in context in an unobtrusive and trustworthy way (e.g., by respecting a user's right to privacy).

Human-centered design is a common practice nowadays, and many methods and tools are at hand to facilitate this enterprise. However, we still see many innovation projects that face difficulties in designing intelligent systems that meet users' needs. The main reason is the complexity associated with the design of such systems. Another reason is that people's requirements become more demanding; users like to have easy-to-use and personalized services and, at the same time, they expect a high assurance of security against, for example, risks of privacy violation.

A Living Lab enables researchers to come close to the users. As an intelligent environment, it exploits its intelligent infrastructures for user-behavior measurement purposes. It moves research out of laboratories into real-life contexts and provides opportunities to nonintrusively study social phenomena in the social and dynamic context of users' daily lives. The Living Lab concept has been acknowledged in Europe as an open innovation instrument appropriate for studying questions related to human behavior and experiences (Mulder, Velthausz, & Kriens, 2008). The Living Lab concept may open up a wealth of possibilities for exploiting the evaluation of intelligent systems. However, according to Mulder and Kort (2008),

> 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). (p. 610)

This article discusses the main challenges (and opportunities) that exist for methodological innovations in a Living Lab setting.

The first challenge this study recognizes is the need for methodological guidelines and tools that effectively combine the intelligent features of Living Labs (e.g., their ability to derive and monitor user experience) with the strengths of methods and tools traditionally used in social science research, such as interviews and focus groups. A second challenge is to develop reliable data-collection systems. At the same time, automatic solutions for capturing and analyzing user behavior and user experiences in Living Lab settings need to rely upon trusted infrastructures capable of building, maintaining, and managing relationships of trust among users, context providers, and service providers. For example, people's sensitivity to privacy issues is increasing nowadays; they would not like to be involved in experiments in which sensitive information was gathered without their explicit consent. The existence of clear and reliable

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privacy-preserving infrastructure must be emphasized also, to convince them that no harm will come of their participation.

A third challenge is to include the full potential of the Living Lab for the benefit of designing and evaluating intelligent systems that (1) perform powerful data analysis methods—in particular, analysis techniques capable of correlating objective behavior and subjective user experience data into relevant design context parameters; and (2) support applications that adapt to user behavior and experience. The main challenge of application adaptation is to achieve desired user experience in different contextual situations while avoiding conflicts and inconsistencies.

In the remainder of this article, we first describe an experimental Living Lab setting designed to gain insight into measuring behavior, in a trustworthy and unobtrusive way, in context. The section also includes a short description of a context-management infrastructure that we use to collect, store, and analyze a great amount of contextual data. We then explain how the analysis of contextual data allows the construction of a behavioral model of users in a nonintrusive manner. Starting from this experimental setting, issues for combining the Living Lab concept with common methods for data collection and data analysis are discussed. In the subsequent section, we review the availability of methods and tools for exploiting user behavioral and experience models in Living Lab scenarios to build and adapt services according to user experience. Finally, we summarize the challenges identified and draw some conclusions.

CHALLENGE 1
Integration of Methodologies and the Intelligent Coffee Corner

The intelligent Coffee Corner is a real-life coffee space in an office building. The Coffee Corner is equipped with reasoning capabilities and intelligent services located throughout a research institute, which employs about 100 workers in two connected buildings. Each building has four floors. Moreover, the employees that work on 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 (see Figure 1).

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 an 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 succeeds if people and technology continually interact (Mulder, van Kranenburg, & Velthausz, 2007).

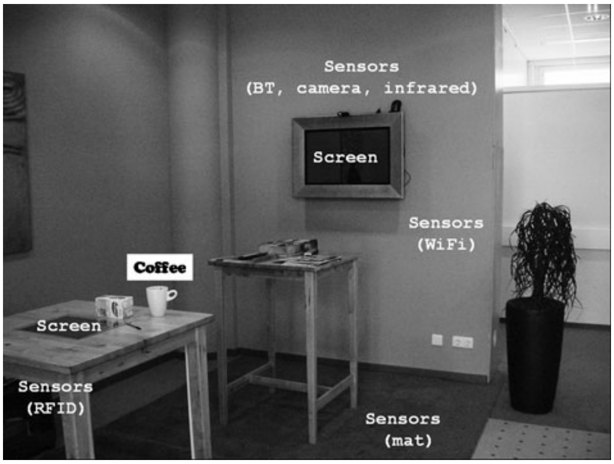

Figure 1. The intelligent Coffee Corner, equipped with sensors such as Bluetooth (BT) dongles, RFID readers, WLAN access points, video cameras, pressure mats, computers, and advanced displays.

In the design process of the intelligent Coffee Corner, user-centered design methods were used—for example, coffee-break brainstorming, questionnaires, surveys, scenarios, contextual inquiries, participatory design, focus groups, paper prototypes, in-depth interviews, and technology probes to gather user needs, expectations, perspectives, ideas, feedback, or inspiration during users' daily activities. For example, for the design of an application that should support sociability among colleagues, knowledge workers were observed during their coffee breaks to gain more insight into their behaviors in the Coffee Corner. The observation showed that, although the shared area is located in a professional environment, while they are in the Coffee Corner the office workers tend to share informal and semiformal information, pertaining to upcoming company presentations, new employees, world news, and so forth. For more detailed information, special coffee-break brainstorming sessions were organized (Fachry, Mulder, Eertink, & Janse, 2007).

Beyond that, a study has been conducted to gain insight into knowledge workers' user needs (Mulder et al., 2007). Data from 12 knowledge workers were analyzed and clustered, resulting in six personas: the butler, the secretary, the guardian angel, the muse, the navigator, and the crystal gazer. These personas have guided the design trajectory of context-aware services offered in the Coffee Corner. For example, to realize the navigator and the crystal gazer, context sources in the context management framework (CMF) that log the user-related data, and context sources that yield location information, have been elaborated upon. These services are explained in the remainder of this work; the navigator and the crystal gazer are introduced below.

The Navigator

The core role of the navigator persona is to communicate one's position in relation to other persons and (nearby) resources such as communication devices, networking resources, printers, and so on.

The Crystal Gazer

The prime role for the crystal gazer is prediction. She reads the tea leaves and predicts when people come and go. She tells you whether or not you should hurry to an ongoing meeting, whether or not a participant of interest to you is about to leave (turning her presence for you into "available"), and she sends notifications of potentially alarming situations, such as upcoming bad weather, when she warns you in a timely fashion to go home. She also alerts you when to go to a certain place at a certain moment, on the basis not only of static route information but of traffic situations (e.g., traffic jams, commuting travel times), and she reminds you of errands to do (e.g., stopping to get groceries on your way home) as well. She also discreetly lets you know when people are having an interesting discussion or conversation you might like to join.

Whereas most of these methods and tools explicitly engage users' involvement, our intelligent Coffee Corner also provides ways to get information from users and gain insight into their behavior in an implicit and less obtrusive manner. Examples of this implicit manner of data collection, which uses the capabilities of intelligent environments, are the following:

1. **Logging**. Information about the use of applications, which ones, and how frequently they are used.
2. **Sensing**. Information about the (physical or virtual) context of the user—for example, the position of users in time.
3. **Inferring**. Reasoning about context information to infer the behavior of people in the Coffee Corner.
4. **User-generated content**. Information that users have created, on their own initiative, for reasons other than those intended by the research.

Both the navigator and the crystal gazer have informed the design of context-aware applications. One of these applications, the *Colleague Radar application*, is explained in the remainder of this article. These personas, together with the sensing capability of the Coffee Corner, demonstrate how implicit and explicit methods can be combined. In this sense, it is possible to come close to the user and how he behaves; the sensed context information is not only used for gaining insight into where a certain colleague is (location, behavior), but also informs the design of the Colleague Radar application.

CHALLENGE 2
Sensing and Management of Contextual Information

To obtain information about users' behavior and users' experience, we make use of the CMF, an infrastructure that enables the collection and the management of context information obtained from various heterogeneous sensors; it is a highly distributed service infrastructure that enables context-sensitive applications to discover and obtain context information (van Kranenburg, Bargh, Iacob, & Peddemors, 2006). Context information is built upon basic sensed data. Typical sensed information includes GPS location coordinates, WLAN access point associations, RFID reader data, Bluetooth scan data, desktop keyboard typing status, presence information, and Outlook calendar meetings.

The CMF collects raw data from these context sources, and processes the data by fusion and reasoning to infer high-level and/or high-quality context information. High-level contextual data are thus composed in the CMF from the available low-level sensor-originating data. In other words, various reasoning components fuse sensed information to higher semantic levels, and each reasoning component can use its own internal algorithm and inference mechanism. The CMF's architecture is also highly extendable; components offering additional ways of combining sensor data into innovative contextual types of data can be added to the CMF. For example, the CMF can easily include a new component that provides services with the number of people in the Coffee Corner or in the building.

Service providers can interface their applications with the CMF and can utilize the high-level context information it provides to design and offer context-sensitive services. For example, a proximity-aware service can rely on the CMF to automatically detect the presence of a user and authenticate his/her identity (up to a certain level of assurance), depending on the location of the user's identity tokens, such as a mobile phone or employee badge. Using contextual information, the service can seamlessly offer a customized service that better matches the user's profile and requirements.

For services to be customizable to any given situation or user needs, advanced reasoning algorithms are required that can deal with heterogeneity, partial information, and resource limitations. Key elements for reasoning approaches are for the reasoning to be centered around the person; for lightweight ontologies to be used with a shared understanding of the meaning of the context information delivered by the CMF; for learning capabilities to use very minimal explicit user input (implicit learning); for simple world models, if beneficial, to be used; and for there to be the means of coping with partial information.

Privacy is essential in context sensing and management infrastructures and needs to be an integral part of the architecture. In CMF, an overlay framework takes care of aggregating context information per entity by using specialized broker components. The use of broker components allows the CMF to implement policy-based access control mechanisms. Usage and privacy-preserving policies, managed by the CMF through the broker components, can be forced against a service's request for contextual data. In other words, services are not allowed to use contextual data related to a user unless the user has given explicit permission for it to the CMF (cf. Hesselman, Eertink, & Wibbels, 2007). Policy enforcement is then possible in the CMF, at least potentially; proposing effective mechanisms to make the user specify a policy at the right level of abstraction is still a matter of research and beyond the scope of the present article.

In summary, using the CMF, we are able to collect, store, and analyze a great amount of contextual data, and this opens possibilities for advanced user experience and user behavior studies. The CMF has proven to be a robust and flexible underlying infrastructure for several mobile health and office applications.

CHALLENGE 3
Measuring and Predicting Behavior

Sensory data is primarily utilized in context-aware applications that adapt to situational circumstances detected by sensors. One such example is the Colleague Radar application, a location-tracking service that enables an authenticated user to visualize the real-time position of colleagues who have given their authorization to be tracked. Figure 2 shows a screenshot of the application user interface (as it runs in the Coffee Corner). The application's interface is shown on the wall display in the Coffee Corner (see Figure 1).

The Colleague Radar application is an example of presence-aware services that derive great benefits from an intelligent analysis of sensory information. Its identification and authentication mechanism is also designed to be dependent on contextual information. In fact, the Colleague Radar implements a proximity-aware and location-based authentication solution; user authentication is processed in an unobtrusive manner, on the basis of the locations of the different identity tokens (e.g., an RFID employee card or a Bluetooth phone) that the user is assumed to be carrying when approaching the Colleague Radar wall screen (Hulsebosch, Bargh, Lenzini, Ebben, & Iacob, 2007). Location-based authentication is additionally supplemented with face recognition (with a camera on the wall screen) to provide a multifactor user identification (Hulsebosch & Ebben, 2008).

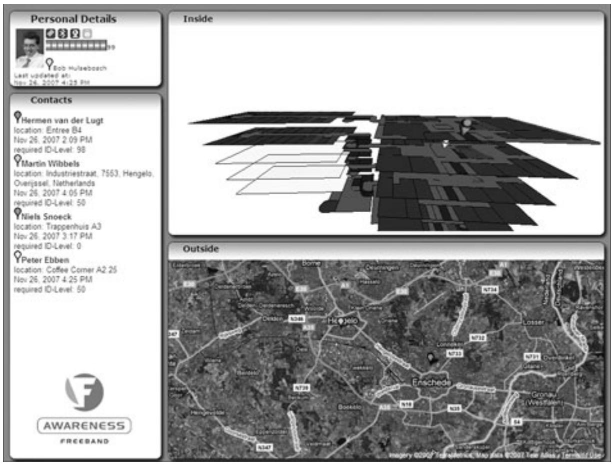

Figure 2. A screenshot of the Colleague Radar application. The top-left panel shows the identification level of the user and the devices that have been used in the identification process (RFID, Bluetooth, face recognition). The bottom-left panel is the list of colleagues who have agreed to have their position shown, giving 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 surrounding area.

The existence of context managing infrastructure like the CMF, and the success we obtained in using contextual information in applications like Colleague Radar, have stimulated our research to investigate the possibility of analyzing sensory information to set up a Living Lab in our office. For this objective, more advanced types of context need to be produced; our focus is currently on behavioral-based contextual information. Behavioral contextual data can be expressed informally—for example: Bob is working, Bob is going to have lunch, Bob is going from his office to the cafeteria, Bob is going to his office by taking the elevator to the first floor, then the stairs to the second floor.

The availability of innovative behavioral models will open new possibilities in context-awareness services. Identification of users may present the behavior as an additional biometrical measure ("what the user is") to increase the reliability of the identification procedures. The authenticity of users' identities may (together with the verification of other user token) be based on the recognition of users' behavior patterns. Behavioral-based contextual information may also open new modalities of customization of context-aware services (e.g., a resource may run into energy-saving mode when it "knows" it is not going to be used by any user). In a Living Lab perspective, new modalities of investigating the preferences of users can use the evidence of their behavior (e.g., people's itineraries, and an evaluation of the time they spent looking at a certain painting, can be used to estimate whether they like or dislike that painting).

To produce automatic behavior recognition, measurement technologies for all relevant behavioral modalities, such as location tracking, body posture recognition, gesture and motion tracking, and sensing of affect, emotion, or cognitive state, are required. Subsequently, the outputs of these technologies (i.e., the raw data) must be analyzed in order to properly determine behavior. This analysis includes inferring behavior from multimodal data (i.e., sensor fusion, feature extraction, and pattern recognition).

High-level context information can be derived from sensors' data. With a high density of different sensors, and through data integration, it is possible to determine temporal structures of events that model a particular aspect of a user's behavior. The evaluation of temporal events can be either momentary (e.g., where he is now), or can be used in a reconstructive (e.g., where he has been) or anticipative (e.g., where he is likely to go) fashion. The latter aspect is related to the prediction of events, which is quite difficult but still possible. Statistical models 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. The intention of reasoning on not strictly temporal context information is to improve the predictions. Bluetooth dongles and desktop activity, as well as Outlook Calendar information, can be used to determine and predict a user's movements. Even

Web cams can be used for location determination, as well as for identification purposes.

We can distinguish at least three different approaches in processing raw data into behavioral models. The first approach consists of building a model of past behaviors—where people have been, how long they have stayed somewhere, which pathways they have chosen, and so on. When location data are also coupled with identification information (e.g., the position of a company Bluetooth phone is traced, and the owner of the phone is known within the company), the behavioral model granularity can be set at the level of individual identities (e.g., where Bob has been; how long he has stayed somewhere). The availability of past behavior can be used in marketing analysis or to improve the quality of a service, but not for realizing self-adapting services.

A second approach targets real-time behavior. One general methodology consists of processing raw sensor data to evaluate the shared expectation of the actual position of an entity. This measure can be useful for building, for instance, automatic authentication or authorization of users, depending on the location of their identity badges. 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. The use of a plotter, for example, can be allowed in a certain meeting room only when the user is actually in the room and taking part in a meeting. When the collection of real-time raw contextual data is combined with past behavioral models, it can be possible to understand whether advanced situational events are occurring—for example, the event behind the question "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 and he is presently in the library." By using model checking algorithms for temporal logics (cf. Clarke, Grumberg, & Peleg, 1999), it is possible to check properties related to a user's past behavior; extending the previous example, we might ask "Has the user forgotten to update his cell phone calendar after a new meeting was scheduled in Outlook?" This could be used to trigger targeted reminders before the user leaves the office.

The third case focuses on models of prediction of behavior. Such models work only with behavioral data that have a statistical regularity and whose predictions can be used to anticipate certain services: for example, the user may be going to exit the building.

The recognition of behavioral-related situations also fosters the design of better and more innovative services. In the previous example, the absent user could be automatically alerted about the meeting on his mobile phone (despite the fact that his local calendar is not updated); if he has forgotten the device somewhere, a close colleague could be contacted instead.

The three aforementioned approaches for processing raw sensory data require obtaining user models that capture the desired aspects of users' behavior. Figure 3 illustrates a step forward, where the derived model is used to govern the adaptation of a service. In this generic process, a model of the user behavior is constructed dynamically from all the following input sources: (1) context information (in turn obtained from sensors); (2) direct user inputs; (3) the way the user and the service interact; and (4) static user preferences. (Obviously, the direct user inputs may be relaxed when addressing unobtrusive adaptation.) The result of the user behavior modeling is "behavioral-based contextual information" that captures dynamic and context-dependent user profiles. Such dynamic user profiles indicate context-dependent user preferences and user experiences. We believe that the importance of the latter (i.e., the user experience indicator obtained from the user behavior modeling process) will increase in the near future

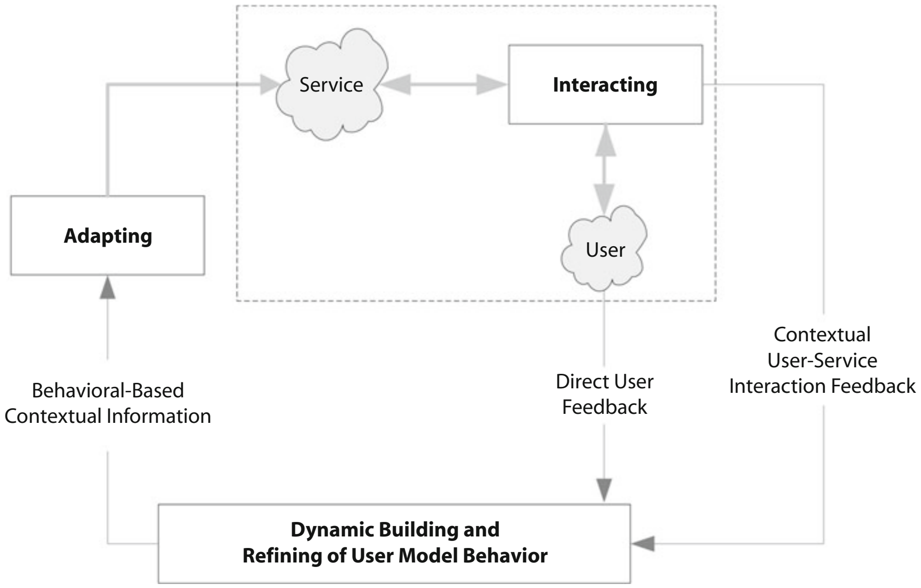

Figure 3. Illustration of a process to derive a behavior model to adapt a context-aware service.

as we witness the emergence of the experience-based service design paradigm.

DISCUSSION AND CONCLUSIONS

The present work has described the main challenges faced (and opportunities presented) in understanding behavior by using sensory data. From the methodological perspective, we explored the opportunities of a Living Lab setting, combining traditional methods of involving users to gain insight into their behavior with the capabilities of an intelligent environment: logging, sensing, inferring, and user-generated content. Another challenge was to develop reliable data collection systems. Automatic solutions for capturing and analyzing user behavior and user experiences in Living Lab settings need to rely upon trusted infrastructures, capable of building, maintaining, and managing relationships of trust between users, context providers, and service providers. In order to include the full potential of the Living Lab as described here, we need to cope with the performance of powerful data analysis methods—in particular, analysis techniques capable of correlating objective behavior and subjective user experience data into relevant design context parameters. A Living Lab also needs to support applications that adapt to user behavior and experience. The main challenge of application adaptation is to achieve desired user experience in different contextual situations while avoiding conflicts and inconsistencies. The analysis of contextual data in order to infer users' behavior or movement patterns is affected by a number of issues that any Living Lab must carefully take into account. Such critical issues are:

- Reliability and availability of context information: Are contextual data always reliable? What if some information is not available when needed? How to deal with wrongly inferred context or behavior information? Users may stop using a service that does not meet their expectations.
- Fusing different heterogeneous context sources: How to map patterns from source to source? How to fuse nonhomogeneous data—for example, a pattern in a location database with one in a temperature database—to conclude that someone is ill, or has gone running?
- Triggers for behavior: What triggers 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 consistency: This is a prerequisite for answering research questions. In observational research, consistency 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 (2003) discussed 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.
- Determining situational awareness: A situation is an abstraction of context. Context interpretation is needed to determine a user's situations and to subsequently offer the right service. User identity and behavior play an essential role in this interpretation phase. In the Coffee Corner, a fully automatic determination of the situation is needed. This requires reasoning algorithms that take context information, user identity, and behavior into account. Furthermore, these algorithms must also take into account the quality and reliability of the situational assessment and the uncertainty in the user's identity and behavior. The algorithms must be robust enough to be able to deal with such aspects to avoid liability issues.

Apart from 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 multistep 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 for by combining and interpreting contextual information originating from, preferably, a heterogeneous set of context sources. This process results in a gradual reduction of the observation space while enriching the context information. The multistep processing of sensor data into actions and enriched context information is facilitated by the CMF, as described.

The availability of context information gathered from multiple sensor sources provided unprecedented opportunities to study user behavior and experience in a nonintrusive, natural manner. Finally, we are able to study the impact of innovative and intelligent solutions in a natural 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.

AUTHOR NOTE

During the present study, all authors joined the Intelligent Communication team affiliated with Novay. This work was inspired by discussions in the Intelligent Communication team and the work done earlier in the Freeband Awareness project. We thank our team members and our colleagues who have contributed to the Coffee Corner research and the Colleague Radar in particular. Freeband Awareness is part of the research program Freeband Communication (www.freeband.nl). Correspondence concerning this article should be addressed to I. Mulder, Delft University of Technology, Landbergstraat 15, 2628 CE Delft, The Netherlands (e-mail: mulderi@acm.org).

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