Fusion of Multiple Datasets to Support Location-based Services in Retail Applications

Gerrit Kahl, Tim Schwartz, Boris Brandherm
German Research Center for Artificial Intelligence
Campus D3_2, 66111 Saarbrücken, Germany
{gerrit.kahl, tim.schwartz, boris.brandherm}@dfki.de

ABSTRACT

The accuracy of a positioning system is often coupled with its costs, e.g. a costly (and dense) infrastructure leads to a higher positioning accuracy. A current trend in indoor positioning are so-called opportunistic systems, which use an already existent infrastructure, e.g. WiFi access points. These systems are known for an accuracy in the range of several meters. In a retail scenario, this accuracy may be sufficient for so-called macro navigation (finding the right area in a shop of a specific item) but insufficient for micro navigation, i.e. finding an item in a shelf. Especially location-based services cannot be established due to the inaccuracy of the positioning. In addition to this, installed sensors in such environments can detect user interactions, however they often cannot identify the person who is interacting. For example, in our Innovative Retail Lab (IRL), shelves are instrumented with RFID readers, which enable the detection of product placing or removal without identifying the interacting user. In this paper, we describe a method that enables the fusion of such an opportunistic positioning system with shelf interactions and user-related information, such as the contents of a shopping list, to derive a better position estimation on the one hand and an identification and disambiguation of user interactions on the other. This fusion approach is based on Dynamic Bayesian Networks (DBNs). The paper points out how the fusion can be used to provide location-based services.

Author Keywords

Dual Reality, Indoor Positioning, Location-based Services, Dynamic Bayesian Networks, Retail, Sensor Networks, Personalization

ACM Classification Keywords

H.5.2 Information Interfaces and Presentation (e.g., HCI): User Interfaces

General Terms

Human Factors; Management; Algorithms.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.
LAMDa'13 in conjunction with IUI'13, March 19–22, 2013, Santa Monica, CA, USA.

MOTIVATION

The supermarket of the future should provide additional services for customers as well as for employers and store managers in order to compete with online shopping. Web shops have the advantage of knowing users and their actions when they login to the system. The information about users enable services adapted to their needs and preferences. In physical stores, users can be identified using special devices or services, which can for example be installed on their mobile phone. This requires the handling with a further device, e.g. by scanning the barcode of a product. In comparison to online shops, physical stores have the advantage that users can physically interact with objects before buying them and they are independent of a delivery service.

In order to overcome the disadvantage of not being able to take user-related information into account, physical stores aim at bringing personalized services into their realm. One long envisioned service for customers is an automated allergy checker, which notifies a customer when they are attempting to buy a product that contains intolerable ingredients. In order to realize such a service, a system at least has to gain the following information:

1. the item a specific customer has chosen
2. a list of ingredients of the chosen item
3. allergies of this specific customer

A fairly easy way to realize point one is to have customers scan each product using their smartphones before they are putting it in their shopping basket (e.g. by scanning barcode, NFC or RFID). By instrumenting mentioned shopping basket (or whole cart, like the IRL SmartCart [5]), this process can be automated. Ideally, such a notification should already occur as soon as a customer takes an inappropriate item out of a shelf, i.e. before they put it in the cart's basket. This is however easier said than done, at least if the solution should be affordable as well as acceptable for users (e.g. instrumenting users with additional sensors, like NFC-reading gloves is not acceptable). A well established instrumentation in retail-of-the-future scenarios are RFID equipped shelves, which can detect if and which item is removed from a shelf. However, the information provided by the shelf does not contain the user information including *who* took the item. In general, for personalized shopping assistant systems, additional data has to be acquired or inferred. Of course such an attempt also brings up the important question of privacy, which is also controversially discussed in the domain of on-line shops. Within the present paper, we suggest an approach for information fusion to enable personalized shopping assistance including a discussion of privacy issues the approach has to deal with.

The paper is organized as follows: in the next section the needed parts to realize personalized services will be described on a high level. Section 'Towards Implementation' describes already existent parts of our infrastructure and elaborates on an early idea on how to fuse existent sensor reading to enhance their accuracy and to infer needed data. The paper concludes with thoughts about privacy issues, which will hopefully spark a lively discussion on this topic during the workshop.

CONCEPT

In principal, the approach consists of the three components. First of all, the current location of the user has to be estimated based on a positioning system. In addition, user interactions have to be recognized and have to be made available for further processing. And finally, the gathered data has to be combined to infer information needed for personalization.

Rough Localization

A low-cost approach for obtaining locations of users and objects are so-called opportunistic systems, which use an already existent infrastructure, e.g. WiFi. Most of these systems have to be calibrated in a training phase and their accuracy usually decreases over time, as the infrastructure and the environment itself changes. The realistic localization accuracy of these systems is in the range of meters, and is thus more of an estimation of the current area (or room) than a precise position. Our own approach of an opportunistic rough-localization system will be described in Section 'UbiSpot'.

Interaction Recognition

Using sensors in the environment, interactions can be detected. For example, shelves equipped with RFID antennas can recognize all products labeled with RFID tags. By storing all detected IDs for each reading cycle, product removal from the shelf and placing of products into the shelf can be registered. The interaction of product removal can be used to present product-related information. Besides visual presentation of such information on a screen mounted in the shelf, acoustic output can be provided by an accordant service. For example, the Digital Sommelier [8] reacts on the removal of a wine bottle by both visual and acoustic feedback. While the screen displays product-related information including the current temperature of the wine based on external temperature sensors, the wine bottle introduce "itself" by verbal description. These services, however, are not able to provide personalized information. As described in the introduction, an instrumentation of customers would enable the identification of the person who is interacting with the environment. But this would neither be affordable nor acceptable by them. The concrete instrumentation of an exemplary instrumented environment is described in Section 'Innovative Retail Laboratory'.

Information Fusion

The idea of the approach described in this paper is to combine the rough position of the user, the interaction detected within the instrumented environment, and further knowledge about the user (e.g. digital shopping list, list of allergies). Based on this fusion, a more precise user location can be inferred which, e.g., could be used for a navigation service. In addition, the combination of an interaction and the customer who is interacting, enables the provision of personalized services running either on a device owned by the customer or in the instrumented environment. A more detailed description of our approach follows in Section 'Fusion with Dynamic Bayesian Networks'.

TOWARDS IMPLEMENTATION

In order to apply the concept of data fusion to support location-based services – as described above – to the retail sector, we combined several components, which we will describe on a high level first.

UbiSpot

UBISPOT [10] is an opportunistic positioning system as described in Section 'Rough Localization'. In contrast to other positioning systems of that type, UBISPOT does not rely only on WiFi infrastructures, but also takes mobile-cell information and nearby Bluetooth devices into account. The system is thus a so-called *Always Best Positioned (ABP)* system (see also [9]), i.e. a positioning system that can make use of different technologies, combining them when several are available at the current environment. The core algorithm of UBISPOT uses *Frequency-Of-Appearance (FOA)* fingerprinting, which does not rely on signal-strength measurements but instead uses a statistic of how often different senders can be detected in subsequent sensor inquiries. As signal strength measurements are heavily influenced by environmental factors, like air-humidity or the number of people in the room, FOA fingerprinting helps to reduce the impact of these factors. UBISPOT was rigorously evaluated and showed room-level accuracy in environments with many WiFi access points available (see [10]). The system outputs the derived location in form of a unique ID, which is also reflected in a location ontology, containing additional information, e.g. geometrical description of the area, shelves present in the area, products present in the shelves etc..

Innovative Retail Laboratory

We have build up an application oriented retail laboratory for testing end evaluating new assistance systems for the future of shopping. This so-called *Innovative Retail Lab (IRL)* [11, 7] is a living lab operated in cooperation with the large German retailer Globus. Based on several sensors, user interaction with objects of the lab can be detected and processed in several assistance services. Beside sensors and services, also actuators have been integrated in this lab to work like a prototypical supermarket including mechanisms for responding to interactions. The sensors can be classified into four categories, namely electromagnetic sensors (RFID, NFC), optical sensors (cameras, fingerprint), magnetic field sensors (digital compass), and small sensor nodes (temperature, accelerometer). In the same way, the actuators can be clustered in four categories: digital signage (displays, electronic price labels), augmented visualization (steerable projector, mobile phones), acoustic output (speech, spatial audio systems), and electronic gates (roller shutter, entrance/exit gate). The processing of sensor information and the controlling of the actuators is realized by several services.

In order to enable sensor fusion and controlling, all sensors, actuators and services are interconnected using an event-based infrastructure. The *Event Broadcasting Service (EBS)* [4] is a server-client based communication infrastructure. All information to be transferred is encoded in events, then sent to the server and broadcast to all registered clients. On the client side, the events are filtered according to their type passing only those the service has registered for. Afterwards, the events are decoded by the event-clients and the information is provided to the services. The event broadcasting enables the information transmission to multiple services at the same time, which can process the data simultaneously. This facilitates the evaluation of new services and updates before installing them in the physical environment. The EBS is implemented in Java while the event is encoded in XML before transmitting to the server. Using XML serialization, also other programming languages can be used to send and receive events by implementing the (de-)serialization and filters for the events. For sensors with only low computing power, a web interface for sending events is also provided by the EBS infrastructure. Based on a simple http-request containing all information to be transmitted, the corresponding event is generated, transferred to the server and broadcast to all clients. One specific client receiving and processing all events is the so-called Management Dashboard [6], which aims at being a monitoring and controlling tool for smart environments.

Fusion with Dynamic Bayesian Networks

Dynamic Bayesian Networks

Bayesian Networks (BNs) are a computational framework for the representation and the inference of uncertain knowledge. A BN can be represented graphically as a directed acyclic graph. The nodes of the graph represent probability variables. The edges joining the nodes represent the dependencies among them. For each node, a conditional probability table (CPT) quantifies these dependencies. *Dynamic Bayesian networks (DBNs)* are an extension of Bayesian networks. With a DBN, it is possible to model dynamic processes, e.g. processes that evolve over time: Each time the DBN receives new evidence, a so called time slice is added to the existing DBN (see also [3]). In Figure 1 the structure of the Dynamic Bayesian Network that we want to use in our example application is shown.

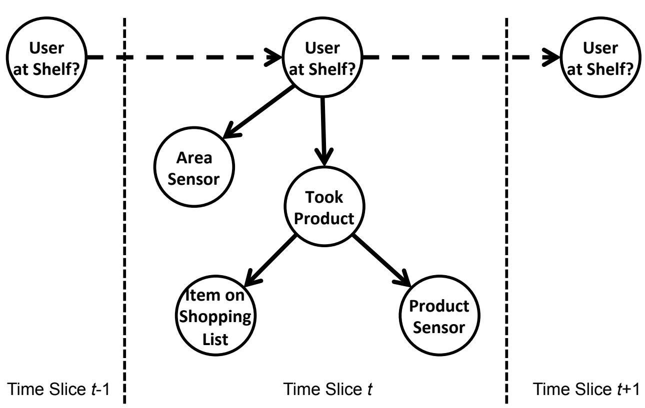

Figure 1. Dynamic Bayesian Network for the fusion of multiple datasets for retail applications.

In general, nodes in a DBN are ordered from cause to effect. In our example, if a customer is in a specific area (cause) (Node *User at Shelf*) then the positioning system will report this area with a certain probability (effect) (Node *Area Sensor*). Being in this area also increases the probability that the costumer takes out a product from a shelf which is in this area (effect) (Node *Took Product*). At the same time, the *Took Product* node is also a cause: If the customer takes out a product, then the probability for both events, that the product is on the shopping list (Node *Item on Shopping List*) and that a product-sensor reports that action (Node *Product Sensor*), increases. In our scenario we do not observe the causes but the effects, i.e. the Nodes *Area Sensor*, *Item on Shopping List*, and *Product Sensor*. The use of DBNs enable the calculation of the likelihood that a user is in front of a shelf given the respective sensor readings. In order to compute the most likely position of each costumer, we have to combine several of these DBNs. This approach with modularized DBNs is similar to the ones as reported in [2, 1, 3].

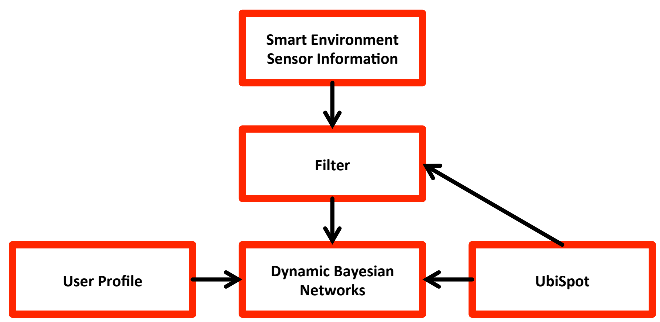

Figure 2. Architecture of the service used for sensor fusion

In order to decrease the number of DBNs to be built and therefore to reduce the computing power, we filter the sensor information first according to the position calculated by the location service before passing it to the DBNs. Figure 2 illustrates the data flow between all components used for the fusion.

DISCUSSION

In this paper, we have presented an early draft of how to combine (or fuse) data stemming from different sources in an instrumented supermarket-environment to gain more detailed information. The bits and pieces of this proposed approach are already implemented, but the combination is still to be realized. So far we just considered how to do the computations given that all the necessary data is available and were not taking care about privacy issues. Before we progress, we want to discuss this important question of privacy in this workshop.

Figure 3 shows two possible realizations of an overall architecture. The solid lines depict the realization as an ‘extrinsic’

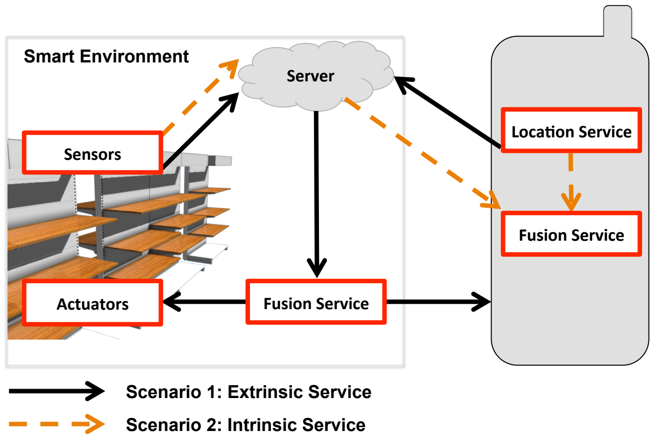

Figure 3. Architecture including information flows for extrinsic and intrinsic scenarios

service, while the dotted lines represent an 'intrinsic' service. In the extrinsic case, the shop's environment and the user's personal device would send their data to a central server belonging to the shop. All further computation would be done on this server. This realization comes close to those currently used in online-shops, but it may very well be argued that this violates the privacy of the customers.

In order to protect the privacy of users, the intrinsic version might be better suited. In this version, all data is collected by the customer's mobile phone and the data fusion algorithms would also be executed on that device. The distribution of shop data can be done using the EBS, where a user could subscribe to all shelf-events happening in their current area. By following this approach, only the user's device would gain a better position information of its own user and can identify its user's actions and can thus react accordingly. If the user is willing, they could also share this information with the shop, e.g. to gain access to other services or to gain price reductions. However, this would also mean that all the shelf interactions are freely available in the market, which could be a potential security-breach that could be used for industrial espionage. A third option not illustrated in Figure 3 may be to have a trusted service, run by a third party, which collects data from both, the shop and the customer, and that has the capability to anonymize certain information while forwarding them.

ACKNOWLEDGMENTS

This research was funded in part by the German Federal Ministry of Education and Research under grant number 01IS12050 (project Software Campus) and the *EIT ICT Labs*. The responsibility for this publication lies with the authors.

REFERENCES

1. Brandherm, B., Prendinger, H., and Ishizuka, M. Dynamic bayesian network based interest estimation for visual attentive presentation agents. In *Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS-08)*, vol. 1 of *AAMAS '08*, International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC (5 2008), 191–198.
2. Brandherm, B., and Schmitz, M. Presentation of a modular framework for interpretation of sensor data with dynamic Bayesian networks on mobile devices. In *LWA 2004, Lernen Wissensentdeckung Adaptivität*, A. Abecker, S. Bickel, U. Brefeld, I. Drost, N. Henze, O. Herden, M. Minor, T. Scheffer, L. Stojanovic, and S. Weibelzahl, Eds. (Humboldt-Universität zu Berlin, Germany, 2004), 9–10.
3. Brandherm, B., and Schwartz, T. Geo Referenced Dynamic Bayesian Networks for User Positioning on Mobile Systems. In *Proceedings of the First International Workshop on Location- and Context-Awareness (LoCA)*, T. Strang and C. Linnhoff-Popien, Eds., vol. 3479 of *LNCS*, Berlin, Heidelberg: Springer (2005), 223–234.
4. Kahl, G., and Bürckert, C. Architecture to enable dual reality for smart environments. In *Intelligent Environments*, IEEE (2012), 42–49.
5. Kahl, G., Spassova, L., Schöning, J., Gehring, S., and Krüger, A. IRL SmartCart - A User-Adaptive Context-Aware Interface for Shopping Assistance. In *Proceeding of the 15th International Conference on Intelligent User Interfaces (IUI-11), February 13-16, Palo Alto,, CA, United States*, ACM (2011).
6. Kahl, G., Warwas, S., PascalLiedtke, Spassova, L., and Brandherm, B. Management Dashboard in a Retail Scenario. In *Workshop on Location Awareness in Dual and Mixed Reality. International Conference on Intelligent User Interfaces (IUI-11), February 13, Palo Alto,, California, United States*, G. Kahl, T. Schwartz, P. Nurmi, E. Dim, and A. Forsblom, Eds., Online-Proceedings (2011), 22–25.
7. Krüger, A., Spassova, L., and Jung, R. Innovative Retail Laboratory – Investigating Future Shopping Technologies. *IT - Information Technology 52*, 2 (2010), 114–118.
8. Schmitz, M., Baus, J., and Dörr, R. The Digital Sommelier: Interacting with Intelligent Products. In *Proceedings of 'The Internet of Things'*, C. Floerkemeier and M. Langheinrich, Eds., LNCS 4952, Springer-Verlag Berlin Heidelberg (2008), 247–262.
9. Schwartz, T. *The Always Best Positioned Paradigm for Mobile Indoor Applications*. PhD thesis, Saarland University, January 2012.
10. Schwartz, T., Stahl, C., Müller, C., Dimitrov, V., and Ji, H. UbiSpot – A User-Trained Always Best Positioned Engine for Mobile Phones. In *Proceedings of Ubiquitous Positioning Indoor Navigation and Location Based Services (UPINLBS'10)*, IEEE (2010), 1–8 (online publication, no pagination).
11. Spassova, L., Schöning, J., Kahl, G., and Krüger, A. Innovative Retail Laboratory. In *Roots for the Future of Ambient Intelligence. European Conference on Ambient Intelligence (AmI-09), 3rd, November 18-21, Salzburg, Austria*, o.A. (2009).