Resolving Users' Behavior Modeling Ambiguities in Fuzzy-Timed Smart Homes Using Only RFIDs

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Summary
Context aware systems successfully exploit the knowledge of the users' actions—presumably in concordance with the environmental parameters of the smart space that they dwell in such as, their location inside the smart space, current time, etc—in providing ambient-intelligent services like automatic, reactive lighting-appliance control and proactive temperature control. In the past, this kind of intelligence has been realized using high-end sensing technologies like video cameras, microphones and environmental sensors such as pressure sensing pads, ambient light-level sensors, temperature sensors, etc. In this paper, we attempt to realize location, time and behavior aware smart spaces using only Radio Frequency Identification Device (RFID) Technology. RFIDs have been effective in object and people tracking, but using RFIDs results in ambiguities in inferring users' activities accurately. We propose to resolve this ambiguity using Bayesian Belief Networks (BBNs). We employ a learning system that models time as fuzzy slots to assist users' location prediction. Our system uses an unobtrusive, negative reinforcement learning (NRL) technique that learns users' behaviors without querying the users of their actions—as typically been done in previous implementations to improve prediction accuracy. The key contributions of our work are that we have proposed a novel method for modeling users' behaviors using RFID technology and shown the experimental results of the same.
Key words:
RFID sensing, Activity Recognition, Unobtrusive Learning, smart space, Ambient-intelligence (AmI)

1. Introduction

Ambient Intelligence is actively researched upon [1] [11-15] in the field of Ubiquitous Computing with an explicit focus on contexts. In the era of personal computing, computers were at the center when it came to providing services for the users; now with ubiquitous computing—the era of one-person-multiple-computers—the computers adapt to the users and the services they offer are user-centric. The computers are made to work at the background. This is achieved by acquiring contextual-data with sensors: video camera, microphones, active-badges and the like; and using this information to learn about the users' environment and their behavioral aspects over time. Our learning algorithm predicts the next location—typically, the next room the user would move. This knowledge is exploited for triggering appropriate actuators using home automation interfaces like X10 modules. In the literature, Context awareness has been classified [10] into five categories - Location Awareness, Time Awareness, User Awareness, Activity Awareness, and Physical Awareness. Peer implementations of context-aware Systems have realized ambient-intelligence in their own unique ways.

More often than not, users' time and location information are the most used categories. The limitations of using high-end sensors such as audio and video--when it comes to providing context-aware services—are that they are difficult to deploy and are expensive. Moreover, these sensing technologies are relatively immature to be embraced by the people today in their homes for context-aware services. Tracking people using sensors or sensor networks demands a sophisticated communication network which may not be available in the home segment. Past research has shown that tracking people over small distances using hand held devices like mobile phones is a bit impractical. We propose to use RFID technology by exploiting its binary nature (presence or absence). Hence, we feel RFID would bridge this technological gap successfully.

Our system provides services by considering these contexts: location, time, uses and the users' activities. Location and User awareness can be realized by tagging appliances and significant objects placed in the smart-space with RFID tags and users with portable medium range RFID readers.

In a major departure from current methods, we equip the users with RFID readers and use the inexpensive tags as the location trackers. In other words, each tag corresponds to a location and the movement is tracked by correlating the data from such locations. This way we made our implementation cost effective by bringing down the number of RFID readers required to the total number of users of our smart space.

When a user is near a location, tagged with and RFID tag, his RFID reader would transmit the location detected. The entire system works on an event driven programming basis such that any activity in the system triggers actions in the overall environment. Time-awareness is achieved by considering the current time in determining the context. Our system realizes time-awareness by using Fuzzy time slots. Activity awareness is difficult to implement by using only RFID sensors. The paper, hence, proposes a Bayesian Belief Network (BBN) over objects the user touches to identify the exact activity. Overall, the tags are invisible and embedded in the environment and the entire system goes a small way in realizing the dream of Mark Weiser for ubiquitous computing. [16]

In AmI, real time Context awareness alone is not usually sufficient: many services also require successful prediction of future contexts. Services like proactively switching-on the air-conditioning system should be done before the user actually enters the room. This way, the users would experience optimal cooling conditions immediately after entering the room. The paper proposes a Fuzzy timed Markovian prediction for services requiring such a gestation period. We implement an unobtrusive learning system which does not question the users while learning.

The other situation is where the behavioral outcomes are unpredictable due to multitude of choices. For example, a user at the entrance to a residence may decide to use the car, watch TV or enter another room. In such a situation, the behavior is a combination of location, time, previous context and the actions of other users in the vicinity. These are handled by the BBN system.

2. Issues

Successful realizations of Ami in the past have relied upon video cameras [1], pressure pads [6], microphone arrays [8] and other sensors. They can identify people, location and their activity fairly accurately but are very costly to implement and implementation is difficult. However, RFID sensing has also been used successfully in tracking people [3] [4]. Since they identify only people and their location, inferring activity becomes difficult. The uncertainty associated with inferring the users' activities should be clearly modeled using appropriate parameters.

Many AmI environments implement a prediction system, for activating devices that require a gestation period; that is, those devices that need to be switched-on before the user can physically enjoy the outcomes of such activations. These have been modeled using various methods and Markov model has been found to be good [2]. But these systems consider only discrete time slots. This may not be appropriate for modeling user behavior, as users do not work on discrete slots. So a better time based model was required.

Many learning systems in current in existence are obtrusive [7]. i.e., they ask the user whether to execute an action or not. Users who are new to the system find this obtrusiveness unacceptable. Moreover, such behavior doesn't conform to Mark Weiser's vision [16]. So, the learning system should be modified to be unobtrusive. Our project conceptually is a variation of the Active Badge project in that we use readers on the users and tags embedded in the environment.

3. Solution

To achieve the ideal of Smart Homes, an intelligent human behavior recognition system is needed to monitor a person's movements in a non-invasive manner and predict future actions. In order to accomplish this objective, several aspects of in-home monitoring must be solved. In particular the first challenge is to tag and identify the environment. Then a profile of the user must be built up.

The first challenge is to identify and label objects in the scene. This is a prerequisite for recognizing high level behaviors since behaviors generally involve the manipulation of objects. Unfortunately, traditional object recognition techniques based on the visual appearance of an object are not reliable, especially in cluttered environments.

In our implementation, we propose a unique system of RFID technology for user and location identification. From this, we infer the user's activities. Each user is provided with an RFID-reader bracelet [17]. RFID tags are embedded on to objects at strategic locations—such as refrigerators, furniture, doorways, etc as shown in Fig. 1.

The overall cost [3][4] of these monitoring sensors is very low as RFID tags, which are required in abundance, cost only around 5 cents and the number of readers required is also very less—typically equal to the number of users of the system.

The second challenge is to build up a profile of the occupant's typical daily behaviors in the home. This can be used to detect anomalous behaviors that may be indicative of emergency situations requiring external intervention. Refinements on this technology would facilitate the creation of 'reminder' systems that are capable of providing appropriate assistance without requiring outside aid.

Fig. 1 Dorm Room Showing Possible Locations of Embedded RFID Tags.

The two kinds of services provided by our system are proactive and reactive services. Proactive services are provided for services that need a gestation period before activation. For instance, a room needs to be cooled before a user enters. So if the user is rightly predicted to enter a room, after some time, the air conditioner can be switched on now.

Reactive services provide real time services, such as switching on the appropriate room lights when a user enters during night. This conserves power, though reporting such a finding is beyond the scope of this paper. As our system is time based, lights in rooms will be switched on only during night times. Moreover, we profile every user to personalize the services. This is done because users' choices differ. Some people may wish the television switched on automatically when they sit on the sofa when they are about to watch TV, at a particular slot of time every day. But some may just sit and relax. So based on the users' behaviors, services are provided using their personal choices, past history information and their behavior information associated with them.

3.1 Proactive Services

The rooms in the home are modeled as Markovian states R1, R2 …Rn. Room Transitions are modeled as Markovian state transitions. i.e., room transitions follow Markovian property.

$$Pr(X_{n+1}=x \mid X_n = x_n,\ldots,X_1=x_1, X_0=x_0) = Pr(X_{n+1}=x \mid X_n = x_n) \quad (1)$$

3.2 Fuzzy Timed Prediction

The prediction should be time based as users' actions are time based. Users' movement patterns vary throughout the day. A day is, thus, divided into 4 time slots and a separate Markovian Transition Probability Matrix (TPM) is maintained for every time slot for every user. To predict the next location, the current time slot is identified and TPM corresponding to the current time slot is used for Markovian prediction.

The problem with such discrete time slots is that, when the current time is in the fag-end of a discrete time slot, in the user's point of view the current time should belong more to the next time slot rather than the current time slot.

So we obtain the contributions A and B (A+B=1) of the current time to the slots which are close to the current time. This is obtained from our fuzzy graph shown in Fig.2, which gives the probability that the current time belongs to a particular slot.

Now the factors A and B are to be incorporated in their corresponding TPMs to get a consolidated time aware TPM.

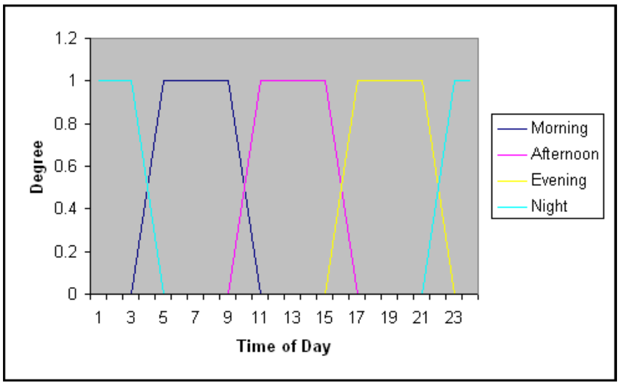

Fig. 2 Fuzziness of Time Slots.

Each of the factors is multiplied with their corresponding TPM and the result summed up to get the Fuzzy Timed TPM.

$$\text{Fuzzy Timed TPM} = A*TPM\_Slot\_A + B*TPM\_Slot\_B \quad (2)$$

From this matrix the next location can be predicted.

3.3 Reactive Services

For identification of the user's actions, all rooms are modeled as Bayesian Belief Networks (BBNs) [5]. Every possible activity is identified using the joint probability of the users of appliances to do that particular activity.

For instance, let C be the event of the reading chair being detected by the reader the user wears. Let T be the event of the reading table being detected and let B be the event of book being detected. So the probability of the user reading a book is the joint probability of the independent events C, T, B.

$$P(\text{User reading a book}) = P(C, T, B) = P(C) * P(T) * P(B) \quad (3)$$

where B is the event of book being detected. T the event of table being detected and C the event of chair being detected. We consider the prob. of book being detected, and the probabilities of chair and table being detected along with the detection of book. We consider T and C as independent events, because detection of chair and table together does not necessarily mean that the user is reading.

If this probability is high enough, the user's action is identified and the services related to that activity will be triggered. Otherwise, those services will not be triggered—assuming that the user's action is un-identifiable. User behavior learning should be unobtrusive. This is achieved by the use of a negative reinforcement agent in our system.

Initially, the prediction is assumed to be correct and a service is offered based on the prediction. If the user location prediction is inappropriate to his behavior, he performs an action not in concordance with the prediction—like a user not being detected in a location even if his profile and contextual information suggest otherwise. Thus the probability of the prediction being correct can be reduced proportionately.

Our system can infer that a user is reading a book when the tags embedded to the reading-chair, the reading-table and his favorite books are detected within the hotspot of the user's RFID reader field. Our system would then switch the table lamp on. If he immediately switches the light off, then it means that he is not currently reading and the system alters its prediction in the future by the above mentioned negative reinforcement cycle.

Let D be the number of times the reading-chair is detected and N be the number of times the user has switched the lamp off, after the lamp has been switched on by the system as a result of prediction.

Now, N/D provides the probability of the chair being detected without the activity being reading. Thus the probability of the chair being detected, with activity being reading is

$$P(D)\ \text{Reading} = 1 - (N/D) \quad (4)$$

4. Implementation

The indoor movement pattern of four people for 180 days was obtained from the publicly available Augsburg indoor location tracking benchmarks [9]. The learning-agent was implemented using JDK1.5 and SQL-Server was used as the database. The agent reads the indoor movement patterns from the indoor location tracking benchmark file, computes the user's next location. The result of prediction is written to another file.

We compared the predicted output and actual behavior to identify the accuracy levels. We measured the accuracy of proactive service as a ratio of number of correct predictions to total predictions. The prediction accuracy is measured against the days of operation. The results are plotted in Fig.3

For reactive services, we implemented the unobtrusive activity identification in our university hostel rooms. The rooms—emulating a smart home space—contain study tables, racks of books, and a few cots all of which are tagged with RFIDs. The BBN takes into account all these objects. Four users were provided with RFID bracelets.

We modeled several activities such as reading, sleeping, dining, etc. In a peculiar case, the activity of a user reading a book when on his bed was modeled. The aim was to resolve ambiguities between the most likely inference from a set of input parameters and the user's action in reality. This involves making the proper inference as to whether the user is sleeping in his bed or reading a novel just before he goes to sleep. There also arose situations where the users were identified as being in the hot zone covering the reading chair, and the one covering the sleeping bed. The bedside reading lamp was switched when the ambiguity was resolved as the user reading despite the fact that he is on his bed. Time information is vital in these scenarios. As the users used the system, the learning agent learnt the activity patterns of the users with respect to time. The negative reinforcement cycles helped to adjust the prediction results when the users behaved unusually, or rather when the prediction wasn't quite accurate. The table lamp was switched on when the ambiguity was resolved to the user reading on his study-chair-table. The number of negative reinforcements was measured for each day. The results are delineated in Fig.4.

5. Results

As shown in Fig.3, the prediction accuracy increased considerably as the period of operation increased. In about 43 days, the prediction accuracy reached an acceptable 74%, and hence learning period can be considered as 43 days. During this learning period, the actuators were not triggered, but the location prediction would continue with negative reinforcement cycles.

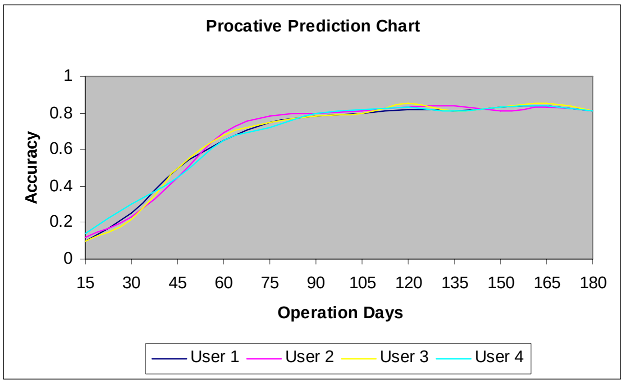

Fig. 3 Accuracy of Time based Location Prediction .

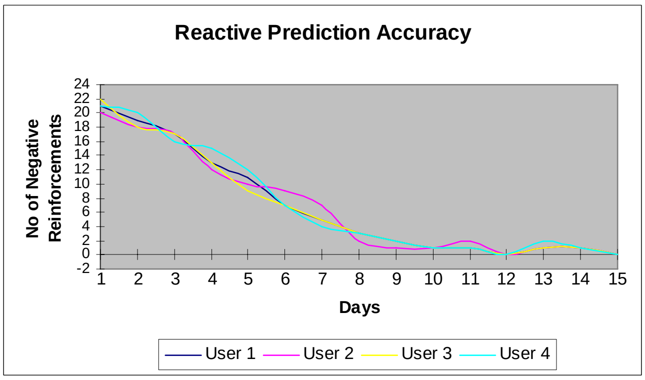

Fig. 4 Reactive Prection Results

After 120 days of operation, the prediction accuracy reached 0.92. i.e., 92% of all the predictions made by our system were right. Compared with non-fuzzy timed implementations such as Augsburg's [2] smart system which resulted in achieved a prediction accuracy of 85%, our system fared much better with the prediction accuracy over 90%.

For the reactive services, the number of negative reinforcements decreased as the days of operation increased as shown in Fig.4. It reached an acceptable minimum of one reinforcement cycle per day within 7 days of operation.

6. Conclusion

Thus, RFID sensing technology alone can be used to realize ambient-intelligence with acceptable levels of accuracy; provided, the learning agent that drives the system uses fuzzy-timed, Markov model for modeling user transitions between rooms and Bayesian Belief Networks for identifying the users' actions. We found the accuracy with which our system was able to resolve ambiguities in identifying the user's behavior to be pretty satisfactory—with the next room prediction accuracy at 92 percent after 120 days of learning period—given the fact that we used only simple and inexpensive RFID tags and a few readers. Therefore, RFID, when used in combination with learning agents based on BBNs and Fuzzy-timed, Markovian model, can be used to realize ambient-intelligence in smart spaces. Though, whether a system implemented along these lines can provide context-aware services with hundred percent accuracy remains to seen, it can be said that RFID sensing has the potential to provide low-cost, robust, easily deployable, context-aware homes in the near future, before real-time audio and video sensing technologies become affordable for the home users.

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