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Improving Prediction Accuracy in Context Aware Smart Homes Using K-Markov Model

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Abstract: Context awareness is a term that refers to knowledge of where, when and what the user does. The study implements all the above forms of context awareness, using only RFIDs in contrast to various expensive technologies like video/audio sensing, pressure pads etc. The paper implements the next room prediction of users based on Fuzzy Timed K-Markov model. Various values of K have been used and the optimal value is suggested. The study also models the uncertainty of user behavior recognition using Bayesian Belief Networks (BBNs) and predicts the user's action using negative reinforcement learning technique. Unlike in previous models where the implementations invariably had the users wear the tags, or the Bracelet readers, but, we use a combination of both as it seemed to help us derive hierarchical contextual information, that is, the context changes that accompany people interacting with each other. The model is also unobtrusive during the learning period. The study in all, aims to realize a context aware Ambient Intelligent system in Smart Home though RFIDs.

Key words: RFID sensing, activity recognition, context-awareness, smart space, Ambient-Intelligence (AMI)

INTRODUCTION

Ambient Intelligence is actively researched upon (Hani *et al*., 2004; Scott *et al*., 1999; Amind *et al*., 1999; Nigel *et al*., 1999; Paul and Anne, 1999; Abhaya *et al*., 1994) 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 (Amind *et al*., 2000) 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

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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.

Unlike in previous models where the implementations invariably had the users wear the tags, or the Bracelet readers (Mike *et al*., 2004), but, we use a combination of both as it seemed to help us derive hierarchical contextual information, that is, the context changes that accompany people interacting with each other. The usage of tags on the people and the readers on the objects suffered the limitations of exorbitant cost of implementation, as every object required a reader. In further development to this concept, the usage of wearable readers was popularized by INTEL (Mike *et al*., 2004). This typically reduced the cost of deployment, as it effectively minimized the number of readers that are required to the number of users in the home. However, this approach had the limitation of limited contextual information gathering, as only the interactions of the users with the tagged objects were captured, and it ignored the all important context changes that take place when people interact with each other. Powered by this novel method of contextual information gathering technique, we equipped the users with tags, in addition to the wearable readers, as was done during the early stages of our research (Mahesh *et al*., 2006) . 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 (Mark, 1991).

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 also the actions of other users in the vicinity. These will be handled by the BBN system.

Issues: Successful realizations of Ami in the past have relied upon video cameras (Hani *et al*., 2004), pressure pads, microphone arrays (Weinsteen *et al*., 2004) 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 (Hugher, 2005;Badri *et al*., 2003). 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 (Jan *et al*., 2005). 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 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, 1991) vision . 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.

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 (Mike *et al*., 2004). RFID tags are embedded on to objects at strategic locations such as refrigerators, furniture, doorways, etc.

The overall cost (Hy Huges, 2005; Badri, *et al*., 2003) 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.

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 study. 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.

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.

$$P(X_{n+1}=x/Xn=x_n,..X_1=x_1,X_0=x_0) = P(X_{n+1}=x/X_n=x_n) * P(X_n=x_n/X_{n-1}=x_{n-1})\ldots.P(X_{n-k}=x_{n-k}/X_{n-k-1}=x_{n-k-1}) \quad (1)$$

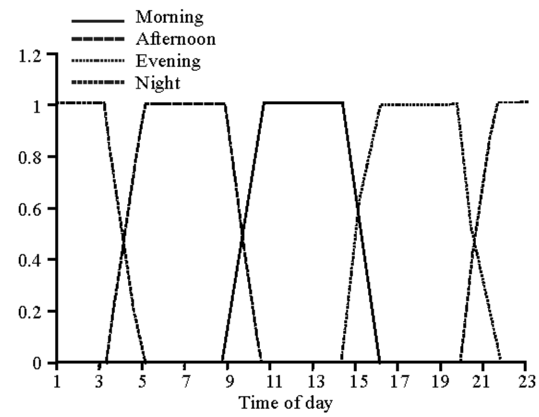

Fig. 1: Fuzziness of time slots

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 probability for previous K room transitions are taken into account. The TPM for the corresponding time slot is made use for finding K products as shown in (1).

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

Fuzzy Timed TPM = A*TPM_Slot_A +B*TPM_Slot_B(2)

From this matrix the next location can be predicted.

Reactive services: For identification of the user's actions, all rooms are modeled as Bayesian Belief Networks (BBNs) (Finn, 2001). Each and 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 events C, T, B.

$$P(B,T,C) = P(B)\,P(T \mid B)\,P(C \mid B,T) = P(B)\,P(T \mid B)\,P(C \mid B).$$
(Since T is conditionally independent from C) (3)

Where B is the event of book being detected. T is the event of table being detected. And C is 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. But we consider T and C as independent events, because detection of chair and table together does not necessarily mean that the user is reading. Fuzzy Timed Prediction

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

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

Implementation: The indoor movement pattern of four people for 180 days was obtained from the publicly available Augsburg indoor location tracking benchmarks (Petzold, 2004). 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. 2.

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. The users were provided with RFID bracelets and RFID tags.

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. 3.

RESULTS

As shown in Fig. 2.1, the prediction accuracy increased considerably as the period of operation increased. In about 68 days an acceptable prediction accuracy of 70% is reached. With k = 2 the learning period

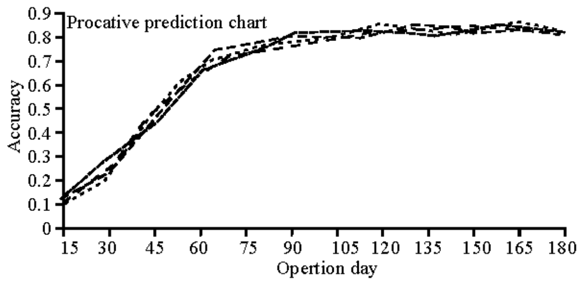

Fig. 2.1: Accuracy of Time based location prediction with k = 2

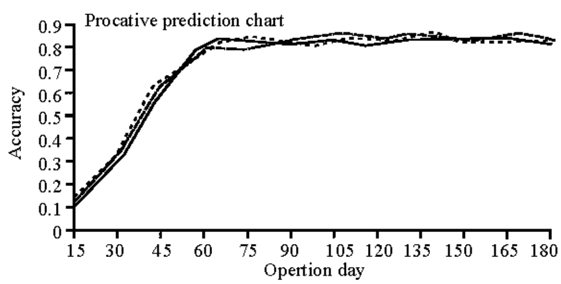

Fig. 2.2: Accuracy of time based location prediction with k = 2

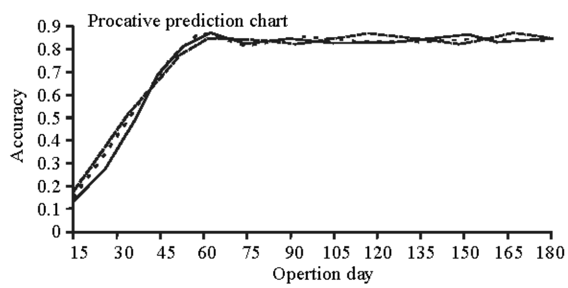

Fig. 2.3: Accuracy of time based location prediction with k = 3

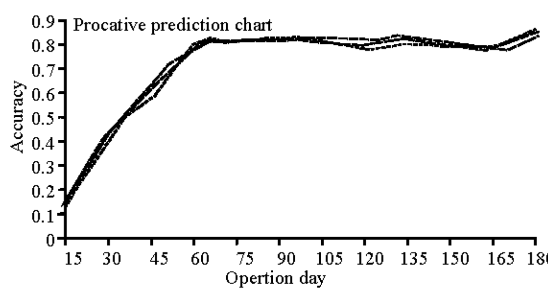

Fig 2.4: Accuracy of time based location prediction with k = 4

decreased, as the prediction accuracy reached 70% in 58 days. With k = 3, it took 45 days to reach 70% accuracy and in 60 days of operation the accuracy reached a peak of 85% and there after the accuracy ranged between 82 to 85%. With k = 4, as shown in the Fig. 2.4, there was not a significant decrease in the learning period and the peak of prediction accuracy did not increase considerably. Therefore, a K-Markov model with k = 3 is sufficient to have a shorter learning period and a very good prediction accuracy of 85%. During this learning period, the actuators were not triggered, but the location prediction would continue with negative reinforcement cycles.

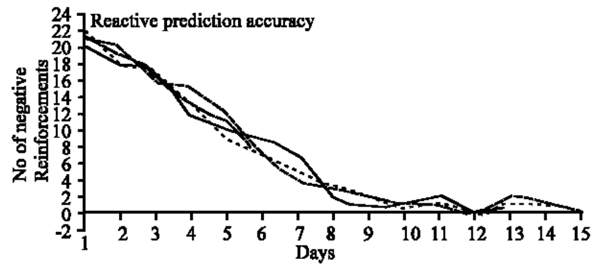

Fig. 3: Reactive prection results

For the reactive services, the number of negative reinforcements decreased as the days of operation increased as shown in Fig. 3. It reached an acceptable minimum of one reinforcement cycle per day within 7 days of operation.

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, K-Markov model for modeling user transitions between rooms and Bayesian Belief Networks for identifying the users' actions. We found the learning period required to reach an acceptable prediction accuracy was 45 days and the peak accuracy went upto 86% within 60 days of operation. The accuracy with which our system was able to resolve ambiguities in identifying the user's behavior to be pretty satisfactory with the number of negative reinforcements reaching zero in 12 days 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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