

Improving RFID's Location Based Services by means of Hidden Markov Models

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Abstract.

Services in Ambient Intelligence systems must adapt to context information and users. So, the development of these services become in a complex task. In this context, we present AmISim: a methodology for the engineering of AmI services. Using AmISim, a LBS based on RFID technology is built. Engineering the service is based on Hidden Markov Models (HMMs) for locations within an intelligent building. The results show that the resolution of a RFID based LBS can be significantly improved and allows by means of the simulator optimally configure the number and location of RFID antennas.

1 Introduction

Ambient Intelligence (AmI) services acquire context knowledge from the environment allowing us personalize and adapt to different users and situations. Besides, to predict contexts allows us to provide proactive services and improve the accuracy of the system. So, the development of AmI systems is a difficult task. To resolve that problem, the approach proposed here is based on AmISim [4], a MABS (Multi-Agent Based Social Simulation) [1] simulator.

Specifically, in this work, the engineering of an RFID (Radio Frequency Identification) Location-Based Service (LBS) is presented for an intelligent building. The work rest on the assumption that users usually have some degree of regularity in their movements through the environment. Under such basis, the system may predict their motion and offer such prediction by a LBS which adapt to particular users. With such approach, a probabilistic framework based on HMMs to location prediction and appropriately deploying all the RFID apparatus are proposed. So, we may improve the system in two ways: 1) obtaining the best location and to trying to optimize the number of antennas and 2) it could be possible, probabilistically, to augment the resolution of the location system.

The rest of the paper is structured as follows. Section 2 describes the methodology for model learning and service building based on AmISim. Section 3 presents the predictive location model with HMMs. Section 4 gives empirical results. Finally, in section 5 some conclusions and future works are given.

2 Model learning and service building

In this approach, we use AmISim, a simulator of entire AmI environment which uses Ubik. Ubik is the simulated part of AmISim. Ubik is a MABS which has capabilities to simulate and to obtain a set of simulated data according to the real environment. The Ubik simulator is integrated with the real part of AmISim, an entire framework

which is able to use semantic technologies for modelling the context model and uses it to provide adaptive and intelligent services.

AmISim is used here in a scenario in which a service can predict workers' locations in an office building. So, we can built the prediction framework based on HMMs and use the set of obtained data from Ubik for training and validating our model. When the HMMs are checked, we can deploy the services over a real environment.

An abstract model of the space in the building is used here. In the abstract model, an undirected graph is compound from the building, where the edges of the graph are doors and crosses, and the nodes are rooms, corridors and stairs. This way, the RFID antennas are situated in the nodes of the graph and each user wears an identification card with a RFID label which identifies his location in a node. In the simulation environment the user's location is known at each moment of time, however this assumption is not true in a real environment.

3 Predictive location model: HMMs

The above section leads us to deduce that an approximation for each not sensorized area is needed. So, a probabilistic framework based on HMMs to built predictive location models is proposed. A HMM for each possible not sensorized destination is modelled and implemented using JAHMM [3], a Java implementation of HMMs.

In these location prediction models, the hidden states model the different possible locations according to the followed path by a worker since the origin to the destination. It is not necessary a direct correspondence between hidden states of the HMMs and nodes of the graph. The observable states are defined by the set the sensorized nodes and they compound sequences of active RFID antennas in sensorized nodes through the worker's trajectory.

Ubik is used to generate the movements of the workers that allow us training and validating the models. Training sets for the HMMs are built by using sequences of active RFID antennas as generated through worker following some path, called traces τ . τ ends when the worker reaches his destination. A node is a destination when the worker spends there more than a threshold for such location. Note that each τ is built from the worker's path starting from his desk (worker's basic location). The traces are classified by their destination and each set of them is a training set of a HMM.

HMM parameters are estimated by using the Baum-Welch algorithm[2]. Thus, learning the HMMs consists on finding the maximum-likelihood estimate of the parameters of the HMM given a group of training samples for a single destination. When the models have been trained, the probability of an observation sequence can be estimated by the forward-backward algorithm[5]. Given a trace, the HMM with the higher probability for such trace allows us to predict the worker's location.

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4 Experiments

The scenario of the experiments is showed in figure 1 a). Figure 1 a) represents a floor of a building and figure 1 b) is the graph built from the building, where the nodes are numbered and the edges, doors and crossings, are represented in red and lined, respectively.

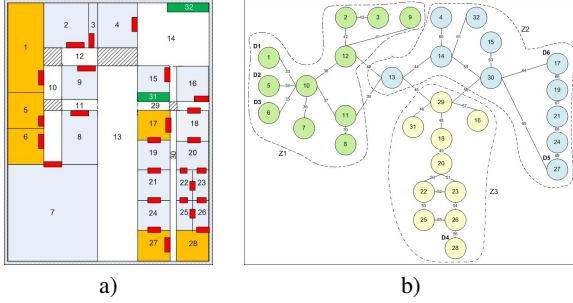


Figure 1. a) Floor of the building b) Graph of the floor

Destinations are represented by label D_i in Fig. 1 b). In the experiments the building is divided into zones: Z_1 , Z_2 and Z_3 . The division into zones shows the fact that in a real environment the workers of the zone Z_i usually will go to destinations in this zone, the nearest destinations. D_1 , D_4 and D_5 are relaxation rooms of the zones 1, 2 and 3 respectively. D_2 is a meeting room and, D_3 and D_6 are warehouses. Each destination is modelled with a HMM.

In order to determine how the decrease of antennas affects the prediction capabilities of the system, in each test, the number of antennas is decreased. Firstly, the antennas of the rooms from each zone are removed. Then, the antennas of the corridors are taken because, as it will be seen in the results, the corridors give more information to the prediction.

The generated HMMs are able to describe all observation sequences of the training set (despite their lengths) and are robust with respect to an unbalanced training data distribution. This feature allows the system a better adaptation to changes in the workers' pattern behaviours, which often occurs in dynamic scenarios like this.

How the number of antennas decreasing influences the precision of the technique allows to decide the minimum number of antennas in order to have an acceptable quality. The results are showed in figure 2: a) represents error rate evolution segregated by destination (y axis) when the number of antennas decreases (x axis) and b) represents averaged error rate (left scale) and averaged precision (right scale).

It is clear from the results that there are dependent destinations. For example, D_1 , D_2 , D_3 are dependent because they share an important part of the graph structure. So, when the service does not predict D_1 when it should, is that it predicts either D_2 or D_3 (see the corresponding error rates in Fig.2 a)).

The decreasing the number of antennas does not affect until approximately a reduction of 23% because the removed antennas have little presence in traces. The same evolution, but inverse, is showed for the precision. As a conclusion, it can be said that removing antennas representing starting points of traces is affordable. However, corridors (i.e. connecting paths of the graph) should not be removed.

5 Conclusions

This work shows how a LBS based on RFID technology is engineered without using any real set up. An AmI simulator is used to

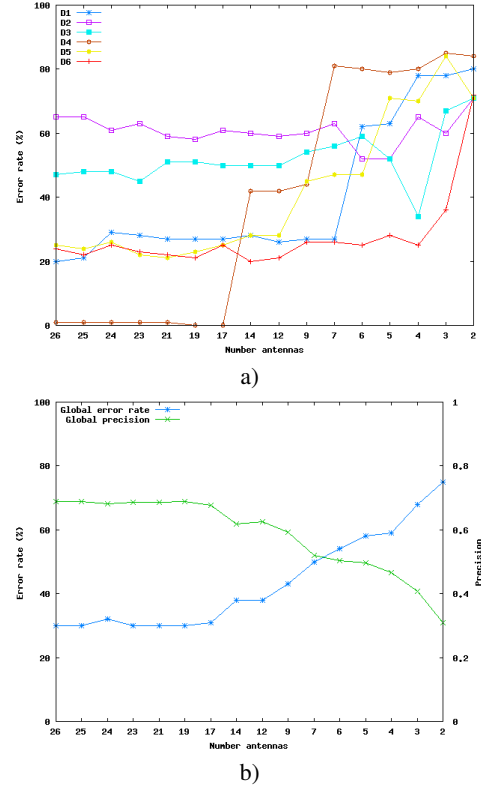


Figure 2. a) Error rates by destination. b) Averaged error rate/precision.

help in the initial engineering of such AmI system. It is illustrated how the simulator is used to generate training data. Such data is used to estimate HMM for any location uncovered by RFID antennas. Experimentation shows that this approach may help on deciding the number and the position of RFID antennas while maintaining an acceptable location power for workers in a building. From this work, one future goal is modelling working activities in order to construct a more detailed context of workers.

ACKNOWLEDGEMENTS

This research work is supported by the FPU grant AP2007-04269, the 09493/FPI/08 grant and in the scope of the Research Projects TSI-020302-2009-43, TIN2008-06441-C02-02, through the Fundación Séneca within the program 04552/GERM/06

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