Prediction of Indoor Movements Using Bayesian Networks

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Abstract. This paper investigates the efficiency of in-door next location prediction by comparing several prediction methods. The scenario concerns people in an office building visiting offices in a regular fashion over some period of time. We model the scenario by a dynamic Bayesian network and evaluate accuracy of next room prediction and of duration of stay, training and retraining performance, as well as memory and performance requirements of a Bayesian network predictor. The results are compared with further context predictor approaches - a state predictor and a multi-layer perceptron predictor using exactly the same evaluation set-up and benchmarks. The publicly available Augsburg Indoor Location Tracking Benchmarks are applied as predictor loads. Our results show that the Bayesian network predictor reaches a next location prediction accuracy of up to 90% and a duration prediction accuracy of up to 87% with variations depending on the person and specific predictor set-up. The Bayesian network predictor performs in the same accuracy range as the neural network and the state predictor.

1 Introduction

We investigate to which extend the movement of people working in an office building can be predicted based on room sequences of previous movements. Our hypothesis is that people follow some habits, but interrupt their habits irregularly, and sometimes change their habits. Moreover, moving to another office fundamentally changes habits too.

Our aim is to investigate how far machine learning techniques can dynamically predict room sequences, time of room entry, and duration of stays independent of additional knowledge. Of course the information could be combined with contextual knowledge as e.g. the office time table or personal schedule of a person, however, in this paper we focus on dynamic techniques without contextual knowledge.

Further interesting questions concern the efficiency of training of a predictor, before the first useful predictions can be performed, and of retraining, i.e. how long it takes until the predictor adapts to a habitual change and provides again useful predictions. Predictions are called useful if a prediction is accurate with a certain

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confidence level (see [14] for confidence estimation of state predictors). Moreover, memory and performance requirements of a predictor are of interest in particular for mobile appliances with limited performance ability and power supply.

The predictions could be used for a number of applications in a smart office environment. We demonstrate two application scenarios:

- In the Smart Doorplate Project [17] a visitor is notified about the probable next location of an absent office owner within a smart office building. The prediction is needed to decide if the visitor should follow the searched person to his current location, go to the predicted next location, or just wait till the office owner comes back.
- A phone call forwarding to the current office location of a person is an often proposed smart office application, but where to forward a phone call in case that a person just left his office and did not yet reach his destination? The phone call could be forwarded to the predicted room and answered as soon as the person reaches his destination.

Our experiments as part of Smart Doorplate Project yielded a collection of movement data of four persons over several months that are publicly available as Augsburg Indoor Location Tracking Benchmarks [12, 13]. We use this benchmark data to evaluate several prediction techniques and compare the efficiency of these techniques with exactly the same evaluation set-up and data. Such a comparison of context prediction techniques has to our knowledge never been done. Moreover, we can estimate how good next location prediction works - at least for the Augsburg Indoor Location Tracking Benchmark data.

Several prediction techniques are proposed in literature — namely Bayesian networks [6], Markov models [2] or Hidden Markov models [16], various neural network approaches [5], and the State predictor methods [15]. The challenge is to transfer these algorithms to work with context information.

For this paper we choose the Bayesian network approach, because Bayesian networks are well suited to model time, and compare the results with the best results from the state predictor method described in [15] and the multi-layer perceptron predictor defined in [18]. The benchmark data allowed next location prediction and duration of stay prediction based on previous room sequences, previous duration of stays, and time and date of room entry. The prediction accuracies of the Bayesian predictor are compared with state and multi-layer perceptron predictor data based on room sequences only.

The next section states related work on context prediction except for our own techniques outlined in section 5.5. Section 3 introduces the application scenarios and the applied benchmarks, and section 4 shows the chosen dynamic Bayesian network model of the application scenario. Section 5 gives the evaluation results. The paper ends with the conclusions.

2 Related Work

The Adaptive House project [10] of the University of Colorado developed a smart house that observes the lifestyle and desires of the inhabitants and learned to anticipate and accommodate their needs. Occupants are tracked by motion detectors and a neural network approach is used to predict the next room the person will enter and the activities he will be engaged. Hidden Markov models and Bayesian inferences are applied by Katsiri [8] to predict people's movement. Patterson et al. [11] presented a method of learning a Bayesian model of a traveller moving through an urban environment based on the current mode of transportation. The learned model was used to predict the outdoor location of the person into the future.

Markov Chains are used by Kaowthumrong et al. [7] for active device selection. Ashbrook and Starner [1] used location context for the creation of a predictive model of user's future movements based on Markov models. They propose to deploy the model in a variety of applications in both single-user and multi-user scenarios. Their prediction of future location is currently time independent, only the next location is predicted. Bhattacharya and Das [3] investigate the mobility problem in a cellular environment. They deploy a Markov model to predict future cells of a user.

An architecture for context prediction was proposed by Mayrhofer [9] combining context recognition and prediction. Active LeZi [4] was proposed as good candidate for context prediction.

All approaches perform location prediction with specific techniques and scenarios. None covers a smart office scenario and none compares several prediction techniques. Moreover, none of the evaluation data is publicly available. Therefore the applied techniques are hard to compare.

3 Application Scenarios and Benchmarks

The Smart Doorplate application [17] acts as testbed for the implementation and evaluation of the proposed Bayesian predictor. A Smart Doorplate shows information about the office owner like a traditional static doorplate. The Smart Doorplate, however, additionally shows dynamic information like the presence or absence of the office owners. If an office owner is absent from his office the doorplate directs a visitor to the current location of the absent office owner. Furthermore it predicts the next location of the absent office owner and the entering time of this location. This additional information can help the visitor to decide whether he follows the office owner or waits for him.

The predicted location information can also be used for switching over the phone to the next location of a clerk. That means when the clerk leaves his office, the system predicts the next location of the clerk and switches over the phone call to this location.

To evaluate prediction techniques in the two described scenarios we needed movement sequences of various clerks in an office building. Therefore we recorded the movements of four test persons within our institute building and packaged the data in the *Augsburg Indoor Location Tracking Benchmarks* [12].

We collected the data in two steps, first we performed measurements during the summer term and second during the fall term 2003. In the summer we

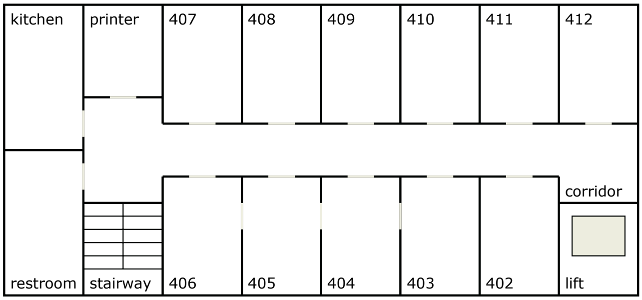

Fig. 1. Floor plan of the institute building

recorded the movements of four test persons through our institute over two weeks. The floor plan of the institute building is shown in figure 1. The summer data range from 101 to 448 location changes. Because this data was too short we started a further measurement with the same four test persons in the fall. Here we accumulated date over five weeks. The fall data range from 432 to 982 location changes. These benchmarks will be used for evaluating the Bayesian predictor in the described scenarios.

4 Bayesian Network Modeling and Implementation

A Bayesian predictor uses the conditional likelihood of actions represented by variables applying the Bayesian formula on a Bayesian network model. A Bayesian network is a directed acyclic graph of nodes representing random variables (X_i) and arcs representing dependencies between the variables. In case there is an arc from X_1 to X_2 then node X_1 is a parent of node X_2. Each variable takes values from a finite set and specific probabilities for those values. To calculate the joint probability distribution the following chain rule is used:

$$P(X_1, ..., X_n) = \prod_{i=1}^{n} P(X_i|Parents(X_i))$$

In order to predict a future context of a person, the usage of a dynamic Bayesian network was chosen. This network consists of different time slices which all contain an identical Bayesian network. The nodes between time slices are connected with arrows to represent dependencies among these time slices.

In our case we predict future locations of a person and additionally the duration of stay and the time when the person is probably changing to a new location. Our application scenario is modelled by the dynamic Bayesian network shown in figure 2. This network exemplarily shows three time slices at time $t-1$, t and $t+1$ but actually there is no limit of time slices in the past or in the future. Since a Bayesian network is assigned to each person in the system, the person doesn't appear as a variable in the network.

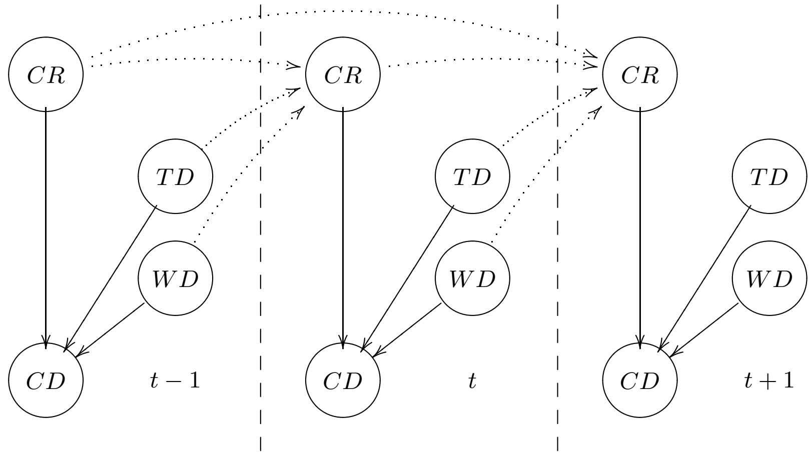

Fig. 2. Dynamic Bayesian network with dependencies between different time slices (dotted arrows)

In each time slice the current duration (CD) basically depends on the current room (CR) of the person. The current room essentially depends on the sequence of the last n rooms visited by the person. Thus the CR's from previous time slices are connected to the CR in the current time slice. The time of day (TD) and the weekday (WD) are also important for the prediction of a person's specific behavior. For this reason CD is closely linked to the current TD and the current WD. The current room also depends on those two influences but from the previous time slice.

5 Evaluation

5.1 Location Prediction

Our first set of evaluations concerns the prediction accuracy and the quantity of performed predictions for next room prediction including and excluding predictions from own office. To predict the next location when somebody leaves his own office is particularly hard, but important for the scenario of phone propagation. Otherwise, for the Smart Doorplate scenario of a visitor standing in front of an office with an absent office owner, it is only interesting if (and when) an office owner comes back or proceeds to another location - and not where a present office owner will go when he leaves his office.

There are two additional factors that influence the evaluation results. First, at the very start the prediction table is totally empty and a useful prediction cannot be done. When a move from a certain office to another has never been done, we cannot predict it. Thus we exclude from the prediction results given below all cold start predictions where we find an empty entry in the prediction table. As consequence the total number of predictions – called quantity – decreases, but the prediction accuracy increases since the prediction accuracy is defined as ratio of the number of correct predictions to the total number of predictions.

Second, the prediction will still be unconfident, when only very little data about previous moves of a person is known to the predictor. In many application cases it is better to perform no prediction instead of a wrong prediction. A predictor trained with data of several weeks will be better than an untrained predictor. We will start our evaluations with untrained predictors using the fall benchmark data only and show how much a predictor trained with the summer benchmarks data improves for the predictions of the fall data.

Evaluation set-up 1: Next location prediction without training, predictions from own office included. Table 1 shows the results of next location prediction of the four test persons excluding empty predictor entries and without training. The prediction accuracies (and quantities) with a history of 1 to 5 rooms are shown separately.

Table 1. Prediction accuracy of location prediction in percent (quantity of predictions in parentheses in percent) with predictions from own office included

	1 room	2 rooms	3 rooms	4 rooms	5 rooms
Person A	55.39 (95.35)	55.61 (87.91)	48.65 (71.63)	51.79 (54.42)	35.38 (33.49)
Person B	56.93 (97.15)	53.65 (90.24)	50.42 (76.22)	53.94 (58.33)	48.10 (38.62)
Person C	43.69 (97.59)	44.73 (87.72)	38.71 (67.98)	48.28 (47.15)	35.48 (28.07)
Person D	50.14 (97.24)	50.61 (87.56)	50.79 (70.51)	51.74 (53.23)	45.28 (36.64)

The results show for most persons an improvement of accuracy if the room sequence is increased from one to two rooms. For person D the accuracy increases up to 4 rooms, whereas the correct predictions of persons A and C decreases after 2 rooms, and for person B already decreases after 1 room. The explanation is simply that person B repeats less often a long room sequence – perhaps a specific habit of person B.

For predictions based on longer room sequences the quantity of predictions decreases because the cold start predictions, which are excluded from the table, concern also the predictions that could be done with less rooms. In particular the number of predictions for person C decreases extremely for 5 room sequences. A low quantity means that most of the predictions are empty because the system is in the learning process. A high quantity shows that the system already knows many patterns and delivers a prediction result. Because of this a larger data base could improve the quantity.

Evaluation set-up 2: Next location prediction without training, predictions from own office excluded. The second evaluation set-up ignores predictions if a person is in his own office. The results in table 2 show that the prediction accuracy improves significantly in this case.

The predictor of person A reaches an accuracy of about 90%, but the accuracy decreases for a longer previous room sequence. In contrast, the accuracy increases with a longer room sequence for person D, but the accuracy decreases if the

Table 2. Prediction accuracy of location prediction in percent (quantity of predictions in parentheses in percent) without predictions from own office

	1 room	2 rooms	3 rooms	4 rooms	5 rooms
Person A	90.19 (91.15)	89.47 (83.19)	90.47 (59.29)	87.27 (48.67)	88.24 (19.47)
Person B	77.65 (94.83)	80.17 (85.98)	78.18 (64.94)	81.25 (50.18)	78.57 (24.35)
Person C	66.67 (95.88)	67.45 (82.02)	61.19 (59.18)	72.83 (42.32)	70.97 (18.73)
Person D	75.00 (95.43)	75.84 (80.91)	76.07 (61.83)	76.82 (44.81)	76.74 (27.80)

room sequence is longer than four rooms. These results show that the sequence of previous rooms influences the accuracy of predictions, however, the results exhibit no common rule. However, some persons act in certain patterns and a better prediction is made if the patterns are included. Table 2 shows also that the quantity decreases with a longer room sequence. In these cases the predictors deliver good results but very rare.

Evaluation set-up 3: Trained versus untrained next location prediction for two room sequences, predictions from own office excluded. Up to now we considered the predictors without any previous knowledge about the persons. We want to analyze the behavior of the predictors if the predictors will be trained with the summer data of the benchmarks. After the training the measurements were performed with the fall data to compare the trained with the untrained predictors, because the results of the untrained predictors were reached by using only the fall data. The results in table 3 show that the training improves the prediction accuracy. Also the quantity (in parentheses) is higher with training. With these results we can see that a larger data base has a positive effect because the system retains knowledge about certain behavior patterns.

Table 3. Prediction accuracy of location prediction in percent (quantity of predictions in parentheses in percent) with and without training based on two previous rooms, and without predictions from own office

	Without training	With training
Person A	89.47 (83.19)	89.65 (90.27)
Person B	80.17 (85.98)	83.72 (92.99)
Person C	67.45 (82.02)	72.14 (88.76)
Person D	75.84 (80.91)	76.49 (87.55)

5.2 Duration Prediction

Our second prediction target is the duration of a person's stay in the current room (his own office or a foreign room). Again we consider prediction accuracy and quantity, additional influence factors as well as trained versus untrained.

To improve the prediction accuracy we tested the influence of the time of the day and the weekday. The week consists of seven days, so we used the discrete values "Monday" to "Sunday". For sectioning the day we must find good discrete values. When we are sectioning the day in too many intervals, for some intervals there will not be a sufficient amount of data for a good prediction. So we classified the day in four discrete time intervals: morning (7:00 a.m. to 11:00 a.m.), noon (11:00 a.m. to 2:00 p.m.), afternoon (2:00 p.m. to 6:00 p.m.), and night (6:00 p.m. to 7:00 a.m.). Likewise, the duration is partitioned in nine intervals of 0-5, 5-10, 10-15, 15-20, 20-30, 30-45, 45-60, 60-120, and more than 120 minutes. We also tested the influence of the time of the day and weekday on next location prediction, however, without reaching an improvement of the prediction accuracy. Therefore we omit results of these measurements.

Evaluation set-up 4: Duration prediction based on current room and all combinations of time of day and weekday including own office. In our modeled network (see figure 2) the duration is independent of the previous room sequence of a person. Therefore we investigated the influence of the time of day and the weekday based on the current room only (room sequence of one).

Table 4. Prediction accuracy of duration prediction in percent (quantity of predictions in parentheses in percent) including own office

	None	Time of day	Weekday	Both
Person A	53.67 (95.35)	54.74 (88.37)	46.33 (82.79)	44.37 (66.05)
Person B	60.21 (97.15)	59.83 (93.09)	55.84 (89.63)	54.55 (78.25)
Person C	73.93 (97.59)	73.52 (92.76)	72.41 (89.91)	70.09 (76.97)
Person D	53.55 (97.24)	52.42 (90.55)	48.07 (88.71)	45.89 (72.81)

Table 4 shows the results of the duration prediction where the unknown predictions were effectively ignored. The results don't show any improvement if the time of day and the weekday is considered. In almost all cases the prediction accuracy and the quantity decrease by considering the time parameters. The reason for this behavior can be the small data base with small time structure. The quantity decreases since the number of prediction decreases with a higher number of influence parameters like in the case of next location prediction.

Evaluation set-up 5: Duration prediction based on current room and all combinations of time of day and weekday excluding own office. This evaluation set-up ignores predictions of the duration if the person is in his own office. Also in this scenario we investigated the influence of the time of day and the weekday. Table 5 shows that the prediction accuracy is significantly improved opposite the result including the own office (see table 4). Obviously, it is particularly hard to predict the duration of a person's stay in his own office.

In duration prediction the influence of the time of day improves the prediction accuracy for person A, B, and C. The consideration of the weekday doesn't improve the accuracy for all persons. The combination of the time of day and the weekday delivers again better results for persons A, B, and C as predictions without any time parameter. The reason for the impairment of the consideration

Table 5. Prediction accuracy of duration prediction in percent (quantity of predictions in parentheses in percent) excluding own office

	None	Time of day	Weekday	Both
Person A	77.67 (91.15)	84.62 (80.53)	71.25 (70.80)	80.00 (48.67)
Person B	86.38 (94.83)	87.87 (88.19)	83.48 (82.66)	88.20 (65.68)
Person C	83.59 (95.88)	83.97 (88.76)	83.56 (84.27)	83.62 (66.29)
Person D	68.70 (95.44)	68.63 (84.65)	61.42 (81.74)	63.64 (59.34)

of the weekday could be the small data base which contains no weekly structure. If we include more parameters the quantity decreases as expected. So you must find a good balance between the accuracy and the quantity, e.g. it is not meaningful for person B to increase the accuracy from 86% to 88% when the quantity decreases from 94% to 65%.

Evaluation set-up 6: Duration prediction with and without training based on current room and all combinations of time of day and weekday excluding own office. To investigate the training behavior of duration prediction we use the same set up like in the case of next location prediction. We used the summer data for training. Then we compared the results which were reached with the fall data with the previous results which were reached with the same data sets. Except for person B we can see in table 6 an improvement of the prediction accuracy. The quantity is better with training as without training for all persons.

Table 6. Prediction accuracy of duration prediction in percent (quantity of predictions in parentheses in percent) excluding own office with and without training, using parameter time of day

	Without training	With Training
Person A	84.62 (80.53)	85.58 (92.04)
Person B	87.87 (88.19)	86.54 (95.94)
Person C	83.97 (88.76)	86.77 (96.25)
Person D	68.63 (84.65)	69.78 (93.36)

5.3 Retraining

A problem of prediction techniques which are based on previous behavior patterns is the learning of behavior changes. Most of the techniques need a long retraining process. Therefore we simulated a behavior change similar to the move of a person to a new office by using 60 data sets of person A followed by 140 data sets of person C. We compared the next room prediction of this set-up with the room prediction results of person C on its own. A well-trained Bayesian predictor needs a long retraining to adapt to the habit change. Therefore we investigated the influence of the number of previous location changes called internal storage which will be used to calculate the conditional likelihood. By restriction the internal storage to 100 or 200 data sets only the retraining can be accelerated. By using the internal storage 100 retraining was done after 90 room changes. In the case of internal storage 200 the retraining ended after 130 room changes. There is no universal rule for determining the optimal size of the internal storage. It depends on the application in which the prediction system is used.

5.4 Storage and Computing Costs

Every person has its own predictor. A predictor must store a sequence of the last r room changes where r is the size of the internal storage. For every room change the room, the time of day, the weekday, and the duration must be stored. In our evaluation set-up there are 15 different rooms which can be stored with 4 bits. For the times of day we need 2 bits, and 3 bits for the weekday. For the duration we used nine discrete values which need 4 bits. Thus the storage costs C of the sequence of the room changes of a person are the following:

$$\begin{aligned} C &= r \cdot (room + time\_of\_day + weekday + duration) \\ &= r \cdot (4\,bit + 2\,bit + 3\,bit + 4\,bit) \\ &= r \cdot 13\,bit \end{aligned}$$

We realized the Bayesian predictor in Java and we tested the predictor on two different systems, a PC with a clock speed of 2.4 GHz and a memory of 1 GB, and a PDA with a clock speed of 400 MHz and memory of 64 MB. The query speed depends on the size of the internal storage for the sequences of room changes. Therefore we used a large internal storage of 2000. The evaluated predictor used a room sequence of five rooms and no time parameters. In the simulation the predictor handled five times the fall data of person B. On both systems we executed this test three times. The results are shown in table 7.

Table 7. Computing time on PC and PDA

	PC	PDA
processor	Intel Pentium 4	Intel PXA250
clock speed	2.4 GHz	400 MHz
memory	1 GB	64 MB
average computing time	5.44 s	1065.41 s
number of predictions	1355	1355
average computing time per prediction	4.01 ms	786.28 ms

5.5 Comparison with Other Techniques

In previous works we investigated other techniques to predict the next location of a clerk. Specially we developed a new prediction technique which is called state predictor method [15]. This method was motivated by branch prediction techniques of current microprocessors and is similar to the well-known Markov predictor. Furthermore we implemented a neural network to predict the next room. The neural network was a multi-layer perceptron with back-propagation learning [18].

Table 8. Prediction accuracy in next location prediction of Bayesian network, Neural network, and State predictor (in percent)

	Bayesian network	Neuronal network	State predictor
Person A	85.58	87.39	88.39
Person B	86.54	75.66	80.35
Person C	86.77	68.68	75.17
Person D	69.78	74.06	76.42

To compare the three different techniques we evaluate them in the same scenario and with the same set-up. We used the trained predictor of set-up 3 (2 room sequence, own office ignored) as basis for all compared techniques. Table 8 shows the prediction accuracy of the different prediction techniques. The Bayesian network delivers the best results for persons B and C and the state predictor performs best for persons A and D.

6 Conclusion

This paper investigated the efficiency of in-door next location prediction and compared several prediction methods. We modelled the scenario by a dynamic Bayesian network and evaluated accuracy of next room prediction and of duration of stay prediction, training and retraining performance, as well as memory and performance requirements. The results were compared with the state predictor and multi-layer perceptron predictor methods. Our results showed that the Bayesian network predictor reaches a next location prediction accuracy of up to 90% and a duration prediction accuracy of up to 87% with variations depending on the person and specific predictor set-up. The Bayesian network predictor performs in the same accuracy range as the neural network and the state predictor.

References

1. D. Ashbrook and T. Starner. Using GPS to learn significant locations and predict movement across multiple users. *Personal and Ubiquitous Computing*, 7(5):275–286, 2003.

2. E. Behrends. *Introduction to Marcov Chains*. Vieweg, 1999.
3. A. Bhattacharya and S. K. Das. LeZi-Update: An Information-Theoretic Framework for Personal Mobility Tracking in PCS Networks. *Wireless Networks*, 8:121–135, 2002.
4. K. Gopalratnam and D. J. Cook. Active LeZi: An Incremental Parsing Algorithm for Sequential Prediction. In *Sixteenth International Florida Artificial Intelligence Research Society Conference*, pages 38–42, St. Augustine, Florida, USA, May 2003.
5. K. Gurney. *An Introduction to Neural Networks*. Routledge, 2002.
6. F. V. Jensen. *An Introduction to Bayesian Networks*. UCL Press, 1996.
7. K. Kaowthumrong, J. Lebsack, and R. Han. Automated Selection of the Active Device in Interactive Multi-Device Smart Spaces. In *Workshop at UbiComp'02: Supporting Spontaneous Interaction in Ubiquitous Computing Settings*, Göteborg, Sweden, 2002.
8. E. Katsiri. Principles of Context Inference. In *Adjunct Proceedings UbiComp'02*, pages 33–34, Göteborg, Sweden, 2002.
9. R. Mayrhofer. An Architecture for Context Prediction. In *Advances in Pervasive Computing*, number 3-85403-176-9. Austrian Computer Society (OCG), April 2004.
10. M. C. Mozer. The Neural Network House: An Environment that Adapts to its Inhabitants. In *AAAI Spring Symposium on Intelligent Environments*, pages 110–114, Menlo Park, CA, USA, 1998.
11. D. J. Patterson, L. Liao, D. Fox, and H. Kautz. Inferring High-Level Behavior from Low-Level Sensors. In *5th International Conference on Ubiquitous Computing*, pages 73–89, Seattle, WA, USA, 2003.
12. J. Petzold. Augsburg Indoor Location Tracking Benchmarks. Technical Report 2004-9, Institute of Computer Science, University of Augsburg, Germany, February 2004. http://www.informatik.uni-augsburg.de/skripts/techreports/.
13. J. Petzold. Augsburg Indoor Location Tracking Benchmarks. Context Database, Institute of Pervasive Computing, University of Linz, Austria. http://www.soft.uni-linz.ac.at/Research/Context_Database/index.php, January 2005.
14. J. Petzold, F. Bagci, W. Trumler, and T. Ungerer. Confidence Estimation of the State Predictor Method. In *2nd European Symposium on Ambient Intelligence*, pages 375–386, Eindhoven, The Netherlands, November 2004.
15. J. Petzold, F. Bagci, W. Trumler, T. Ungerer, and L. Vintan. Global State Context Prediction Techniques Applied to a Smart Office Building. In *The Communication Networks and Distributed Systems Modeling and Simulation Conference*, San Diego, CA, USA, January 2004.
16. L. R. Rabiner. A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition. *IEEE*, 77(2), February 1989.
17. W. Trumler, F. Bagci, J. Petzold, and T. Ungerer. Smart Doorplate. In *First International Conference on Appliance Design (1AD)*, Bristol, GB, May 2003. Reprinted in Pers Ubiquit Comput (2003) 7: 221-226.
18. L. Vintan, A. Gellert, J. Petzold, and T. Ungerer. Person Movement Prediction Using Neural Networks. In *First Workshop on Modeling and Retrieval of Context*, Ulm, Germany, September 2004.