Next Location Prediction Within a Smart Office Building

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ABSTRACT

We investigate the feasibility of in-door next location prediction using sequences of previously visited locations and compare the efficiency of several prediction methods. The scenario concerns employees in an office building visiting offices in a regular fashion over some period of time. We model the scenario by different prediction techniques like Neural networks, Bayesian networks, State and Markov predictors. We use exactly the same evaluation set-up and benchmarks to compare the different methods. The publicly available Augsburg Indoor Location Tracking Benchmarks are applied as predictor loads.

Keywords

context awareness, location prediction, proactive

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, at this time 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 confidence level (see [18] 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 [22] 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 [13, 14]. 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. Moreover, we can estimate how good next location prediction works - at least for the Augsburg Indoor Location Tracking Benchmark data.

2. RELATED WORK

The Adaptive House project [11] 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. [12] 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 [10] 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. AUGSBURG INDOOR LOCATION TRACKING BENCHMARKS

The Augsburg Indoor Location Tracking Benchmarks were derived within the Smart Doorplate project [22] which acts as testbed for implementation and evaluation of the proposed prediction techniques. 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. As example we consider a scenario with Mr. A. and Mr. B.:

> Mr. A. leaves his office and the system predicts the office of Mr. B. as next location. Now Mr. A. is en route to this office.
>
> In Mr. B.'s office the phone rings. He answers the call and says: "No, Mr. A. isn't here." At this moment Mr. A. enters the office of Mr. B. and Mr. B. speaks to the caller: "Oh however, Mr. A. is now here. I give over the phone."

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* [13, 14].

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 recorded the movements of four test persons through our institute over two weeks. 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 different prediction techniques in the described scenarios.

4. COMPARISON OF PREDICTION TECHNIQUES

Several prediction techniques are proposed in literature – namely Bayesian networks [6], Markov models [2] or Hidden Markov models [21], various Neural network approaches [5], and the State predictor methods [19]. The challenge is to transfer these algorithms to work with location sequences.

We currently investigate Neural networks, Bayesian networks, Markov and State predictors. First we chose from the multitude of Neural networks the most well-known, the multi-layer perceptron with one hidden layer and back-propagation learning algorithm. The multi-layer perceptron was chosen because of its general application domain and its popularity in the Neural network research community. Details on the multi-layer perceptron with back-propagation learning were published in [23]. After analyzing more neural networks we decided that an Elman net fits better for solving the next location problem. Elman nets hold a so-called context layer. With this layer the nets are suited to learn sequences. Recent results show that Elman nets are usually better suited than the multi-layer perceptron [9].

In the case of Bayesian networks we started with a static Bayesian network. Afterwards, 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. Bayesian networks are particularly well suited to model time [20].

The state predictor method originates in branch prediction and data compression algorithms that are transformed and adapted to fit the scenario of context prediction. Generally speaking, the prediction principle is derived from Markov chains theory [2]. In [15, 16, 17] several one- and two-level predictors were proposed and evaluated by synthetic benchmarks. In [19] the state predictors were evaluated with the Augsburg Indoor Location Tracking Benchmarks. Moreover we evaluated the well-known Markov predictor.

Table 1 compares the prediction accuracies of the Neural networks Elman net and multi-layer perceptron (MLP), Bayesian network, State predictor, and Markov predictor showing always the best results yielded for each person. The configurations may vary for different person. The configuration details are published in the papers cited above. Typically, there is no superb configuration of a predictor for all persons. The shown prediction accuracies are derived for the first scenario where a visitor will be informed about the potential return of an office owner. That means the accuracies include only predictions when the employee isn't in his own room. Furthermore the following set-up was used: All prediction algorithms were trained with summer data and the accuracies were measured with the fall data (see section 3). The results show that there isn't a universal predictor.

Because of the sometimes unreliable results of predictions it may be sometimes better to make no prediction instead

Table 1: Prediction accuracies of the up to now evaluated prediction techniques

	Elman net	MLP	Bayesian network	State predictor	Markov predictor
Person A	91.07%	87.39%	85.58%	88.39%	90.18%
Person B	78.88%	75.66%	86.54%	80.35%	78.97%
Person C	69.92%	68.68%	86.77%	75.17%	75.17%
Person D	78.83%	74.06%	69.78%	76.42%	78.05%

of a wrong prediction. Humans may be frustrated by too many wrong predictions and won't believe in further predictions even when the prediction accuracy improves over time. Therefore confidence estimation of context prediction methods is necessary. In [18] three confidence estimation techniques for the state predictor method were proposed and evaluated. The proposed confidence estimation techniques can also be transferred to other prediction methods like Markov Predictors, Neural network, or Bayesian networks.

Moreover, also the length of stay is of interest. This can easily be predicted by dynamic Bayesian networks or attached to other predictors as arithmetic mean or median of previous length of stay in the respective room.

5. CONCLUSION AND FUTURE WORK

We evaluated several prediction techniques for indoor location prediction with exactly the same set-up and data. The evaluation shows a variation of prediction accuracies among the different prediction methods as well as within configurations of a specific methods. Prediction accuracies of 70% to 90% could be reached.

In future we will analyze more prediction techniques which could solve the problem of next location prediction, e.g. Hidden Markov models. Furthermore we will develop different hybrid predictor. A hybrid predictor holds a set of simple predictors and chooses a predictor to predict the next location on the basis of a selection criteria. Moreover, we will include length of stay and daytime in all predictors. Also we will generate more benchmark data by an automatic location tracking system.

The prediction algorithms should also be evaluated with other context domains. For example outdoor movement patterns can be used to predict the next region a person will enter. Elevator prediction could anticipate at which floor an elevator will be needed next. Routing prediction for cellular phone systems may predict the next radio cell a cellular phone owner will enter based on his previous movement behavior. The main problem is to get appropriate benchmark data.

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