Poster Abstract: Recommendation-based Smart Indoor Navigation

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ABSTRACT

Localization in indoor spaces has to rely on sensing devices (e.g., Radio Frequency Identification (RFID) readers, WiFi routers, blue-tooth beacons) rather than GPS devices. On the other side, we could build a smart indoor environment that facilitates all types of spatial services with various sensing devices. In this paper, we focus on the topic of spatial navigation.

Due to the complexity of indoor environments, we believe the indoor navigation strategy should not be limited to the shortest path. Taking shopping centers for example, a navigation path should be not only the shortest path, but also an attractive route to the shopper. We aim to build a smart indoor navigation system, which not only learns the user's behavior through previous sensing data, but also enjoys working with heterogeneous devices. Therefore, we propose a novel recommendation based smart navigation strategy with Recurrent Neural Network (RNN). This strategy provides optimal user experience by: 1) Memorizing the user's historical data; 2) Overlapping the navigation with the user's indoor behavior model; 3) Making recommendations based on real-time detections from sensor devices.

CCS CONCEPTS

•Information systems →Location based services;

KEYWORDS

internet of things, indoor navigation, recurrent neural network

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1 INTRODUCTION

People spend most of their time in indoor spaces. Indoor spaces are growing larger and more complex (e.g., multi-functional shopping malls, NYC subways, etc.). Therefore, users will be likely to use spatial navigation mobile apps to find friends or Points Of Interest (POI) in indoor places. However, existing spatial query solutions

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Figure 1: Recurrent Neural Network.

cannot be applied to indoor spaces because of the lack of GPS signals.

The uses of sensing devices have expanded beyond traditional fields and made indoor localization possible. Take RFID technologies as an example. When a tag is in the detection range of a reader, the reader recognizes the tag and generates a reading record. Several types of deviations can be observed from sensor devices, such as sensitivity errors, bias, noise and so on. As a result, the raw data generated by sensing devices can not be used for localization directly. Therefore, we use Bayesian inference based filtering methods, such as particle filters [3], to accurately calculate the position of a tag.

In outdoor spaces, we only have GPS signal. On the contrary, we could utilize all types of sensing devices in indoor spaces. Most of the times, mobile user localization is achieved by WiFi routers, merchandise, equipments, and packages are tracked by RFID tags. We could deploy heterogeneous devices that connect intermittently to one network in the entire building. More specifically, in our research, we focus on improving users's experience by establishing smart indoor navigation. We build a user-specific indoor behavior model for each user at the first place. To achieve that, we use Recurrent Neural Network (RNN) to train and memorize users' historical behavior. RNN is adopted in our system for the following two reasons: 1) The strategy of RNN mimics human's real behavior. Each neuron of the neural network represents a portion of human memory; 2) The loops around hidden layers make RNN suitable for time series prediction. Each loop will pass the information from current step to the next step.

We will also compare RNN with other classic machine learning models, such as Hidden Markov Model and Gaussian Mixture Model.

2 APPROACH AND UNIQUENESS

2.1 Recurrent Neural Network Behavior Model

A strict feedforward architecture does not maintain memory. Any memory effects are due to the way past inputs are re-presented to

Figure 2

Algorithm 1 Recommendation-based dynamic indoor navigation

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1. INPUT: BM (Behavior Model), possible shortest paths
2. OUTPUT: PATH
3. Initialization: start to feed route information into the model
4. for every decision making (path junction) do
5.   if possible choices > 1 then
6.     retrieve the probability of each path from BM
7.     add the path segment with the highest possibility to PATH
8.   else
9.     add path segment to PATH
10.  end if
11.  feed chosen path segment into BM
12. end for
13. return PATH

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the network [1]. As shown in Figure 1(a), a recurrent network has activation feedback enables short-term memory. Figure 1(b) shows a time expansion of RNN. A state layer is updated not only with the external input but also with activation from the previous forward propagation.

Figure 2(a) shows the real implementation of our RNN approach. We use RNN to memorize each user's previous behavior.

2.2 System Design

Indoor facilities always have organized structures. A navigation query will possibly return several shortest paths. Take Figure 2(b) for example, same source and destination might result three shortest paths. In order to select the user's favorite path, we propose to utilize the RNN-based behavior model. We aim to choose the path that fits the model with the highest probability.

RNN-based Behavior Model In Algorithm 1, we explain how to select the best path that fits the user's usual behavior. For each user, we pre-train a Behavior Model with RNN. As the nature of RNN, Behavior Model will be able to predict the probability for all possible choices.

Starting from the user's current location, our system is able to provide dynamic indoor navigation. As we can see from Line 4-12. At each path junction, we are trying to overlap the shortest path with the user's usual behavior (memory). If there is only one shortest path at current path junction, we will add the shortest path to maintain shortest distance. More importantly, we will feed previous path segments into BM to update the model simultaneously.

Recommendation Since our system is a dynamic system with segment-by-segment navigation, it is easy to integrate with the recommendation system. With the development of sensing devices, people are able to acquire real-time sensor signals. Take RFID as an example, most merchandise in super market and shopping malls are attached with RFID tags for stock check. If we deploy enough readers, we will know the movements of the merchandise, and

Figure 3: Varying the number of moving objects.

which items left shelves. We could further deduct the shopper's preference and make recommendations along the shopping path.

In general, with the development of Internet-of-Things, any system should be able to handle heterogeneous sensing signals, and couple with other systems easily. Our system not only provides smart navigation by memorizing historical data, but also enjoys utilizing different sensing devices.

2.3 Uniqueness

While other researchers have made use of indoor sensing devices like RFID and WiFi, to the best of our knowledge there is no previous work that achieves smart indoor navigation. In addition, previous works pay more attention to static queries, while our work focuses on dynamic queries to support IoT settings.

3 PRELIMINARY EXPERIMENTS AND FUTURE WORK

In our preliminary experiments, we test on the setting of an indoor environment with RFID technologies. A number of RFID readers are deployed. Each merchandise is attached with an RFID tag, which can be recognized by any reader when the tag passes the reader's detection range. We carry out preliminary experimental evaluations using the data generated by real-world parameters, and compare the results with other symbolic model-based solutions [2].

We test the effect of particle filters and the Kalman filter with various parameters (e.g. query window size, number of particles, number of moving objects, activation range, continuous query, etc.). We use *PF*, *KF*, and *SM* to represent the curves of the particle filter-based method, Kalman filter-based method, and symbolic model-based method, respectively. Due to limitations of space, we only show 1) the Kullback-Leibler (KL) divergence of range query; 2) hit rate of kNN query by varying the number of moving objects. Figure 3 demonstrates both filtering methods have better scalability than the symbolic model based solution.

Our preliminary results show that particle filters and the Kalman filter are efficient and accurate enough to be utilized in our system.

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