SRC: Dynamic Indoor Navigation with Bayesian Filters

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ABSTRACT

Indoor space navigation has always been an issue without GPS localization. Especially for complicated cases such as emergency evacuation and dynamic navigation, there is no existing efficient solution to the best of our knowledge. Localization in indoor spaces has to rely on sensing devices (e.g., Radio Frequency Identification(RFID) readers, WiFi routers, bluetooth beacons) rather than GPS, and indoor floor plans are more complicated than road networks. Consequently, existing spatial outdoor query techniques are not suitable for this new challenge. However, raw data generated by sensing devices suffers from false negatives and errors. As a result, filtering methods are necessary for accurate localization.

We propose a novel dynamic shortest path navigation strategy to enable efficient navigation for emergency evacuation in indoor spaces. This strategy achieves optimal time efficiency by: 1) using a Bayesian inference based concurrent model, which integrates dynamic shortest path searching into the filtering process, thus achieving an efficient and accurate search for any time-sensitive situation; 2) storing alternative parent nodes along the shortest path search for a fast, dynamic search.

We use both particle filters and the Kalman filter to study which one is more suitable for dynamic environments. In general, we develop an innovative, dynamic shortest path navigation solution based on Bayesian inference localization.

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. In extreme cases like fires or terrorist attacks, indoor spatial navigation could even save lives. However, existing spatial query solutions [2] for Euclidean distances or road networks cannot be applied to indoor spaces because of the lack of GPS signals. Furthermore, indoor floor plans are more complicated with multiple levels involved. 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 [4], to accurately calculate the position of a user.

More importantly, in our research, we focus on dynamic navigation rather than static spatial queries. Dynamic navigation is more suitable for indoor environments for the following two reasons: 1) Indoor routes could change at any time, especially during an emergency, during which a route could be blocked in a short time. In such scenarios, static solutions would not be workable, because the system has to calculate all over again; 2) Sensing devices localization is not as good as GPS. They have to correct themselves sometimes, which will affect the navigation process.

Based on the aforementioned reasons, we apply a concurrent model to Bayesian inference to accelerate dynamic navigation. There are two reasons why we apply this model: 1) In event-driven cases, there is a high possibility that the user is in a room or in a highly-recognizable space. We do not need to know the exact location of a user to navigate; especially in an emergency situation, we need to navigate as soon as possible; 2) Bayesian inference has an updating phase. In time-sensitive cases, it is crucial to take advantage of this phase and accelerate the whole process.

2. APPROACH AND UNIQUENESS

2.1 Design

Our accelerated dynamic navigation has two components: Bayesian-based Concurrent Navigation and Redundant Tracking method.

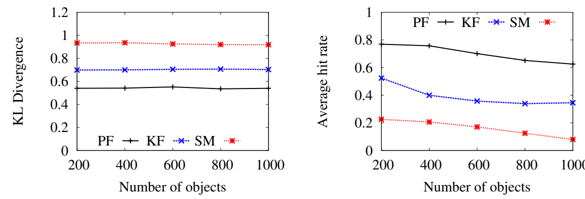
Bayesian-based Concurrent Navigation is based on Bayesian Inference methods, and it is combined with a Bayesian updating phase. More generally, it could be added to any localization method with an updating phase involved. *Redundant Tracking* is applicable to any dynamic queries. It is extremely suitable for indoor spaces.

2.1.1 Bayesian-based Concurrent Navigation

Each time a position is calculated, multiple resamplings /re-calculations are required for Bayesian Inference meth-

Algorithm 1 Bayesian inference-based dynamic navigation

retrieve Obj_s's readings from the data collector
for every second of readings **do**
  Initialization
  Normalize the weights of Obj_s
  Resampling/Re-calculation
  Store locations with weight $> \tau$ (τ is the threshold)
  Redundant Shortest Path Search
end for
return navigation based on weight and location



(a) KL divergence (b) kNN success ratio

Figure 1: Varying the number of moving objects.

ods. In the process of resampling/re-calculation, a user has to wait for a response, which is unacceptable in an emergency. Here, we propose concurrent dynamic indoor navigation combined with Bayesian inference.

We use particle filters and the Kalman filter as examples.

Particle filters Traditional particle filters method consists of three phases: initialization, particles updating, and particles resampling. At first, a set of particles are uniformly distributed in the search area. Then the particles are updated with Gaussian distribution. After updating, the resampling process will remove particles with lower weight and replicate particles with higher weight. In the initial process, a user has to wait enough rounds of resampling for accurate localization. We take advantage of this time period to conduct dynamic shortest path searches on all potential locations. We start as soon as we get the first reading, and search a shortest path from every possible location. We also maintain all possible paths to avoid further calculation.

The Kalman filter The Kalman filter uses a series of measurements observed over time. It assumes an object's speed is a Gaussian variable, and for each reading, the algorithm recursively enumerates all possibilities. At last, the algorithm integrates the *pdf* (probability distribution function) of the object's possible locations. For each update phase, the current priori prediction is combined with current observation information to refine the state estimate. Same as particle filters, we integrate our dynamic navigation into the state prediction phase.

2.1.2 Redundant Tracking Approach

We assume the routes are constantly changing. In order to do the incremental search only, our algorithm uses "redundant" storage to keep track of potential shortest paths along the way. For each visited node, we store λ alternative parent nodes (λ is the number of alternatives, which is a parameter).

Even though redundancy is required for this approach, creating extra storage will not be a burden for the search process because indoor floor plans are relatively smaller than outdoor road networks.

Algorithm 1 shows the general structure to integrate redundant tracking into Bayesian inference. We check all possibilities for each Bayesian updating. When the current possibility is good enough for a search, we execute redundant shortest path search instantly.

2.2 Data Settings

In our research, we focus on the setting of an indoor environment and RFID technologies. A number of RFID readers are deployed along the hallway. A user is attached with an RFID tag, which can be recognized by any reader when the user passes the reader's detection range. The system will store all raw readings generated by readers.

2.3 Uniqueness

While other researchers have made use of Bayesian Inference to localize indoor targets, to the best of our knowledge there is no previous work that combines Bayesian inference with dynamic indoor navigation. In addition, previous works pay more attention to static queries (e.g., kNN, range query), while our work focuses on dynamic queries to support indoor navigation. An approach based on dynamic settings may be more practical for indoor queries.

3. PRELIMINARY EXPERIMENTS AND FUTURE WORK

We carry out experimental evaluations using the data generated by real-world parameters, and compare the results with other symbolic model-based solutions [3].

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 1 demonstrates both filtering methods have better scalability than the symbolic model based solution.

Our preliminary results show that particle filters and the Kalman filter based spatial queries are efficient and accurate enough to extend to dynamic navigation. We will compare the speed of particle filters and the Kalman filter to see which one is more suitable for dynamic navigation.

4. ACKNOWLEDGMENTS

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