A Novel Backtracking Particle Filter for Pattern Matching Indoor Localization

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ABSTRACT

Particle Filter (PF) techniques has been widely used in indoor localization systems. They are often used in conjunction with pattern matching based on Received Signal Strength Indication (RSSI) fingerprinting. Several variants of the particle filter within a generic framework of the Sequential Importance Sampling (SIS) algorithm have been described. The purpose of this paper is to show how a variant of PF, the so-called Backtracking Particle Filter (BPF), can be used to improve indoor localization performance.

The BPF is a technique for refining state estimates based on exclusion of invalid particle trajectories. Categorization of invalid trajectory determined during importance sampling step of the PF. The BPF can also take advantage of available building plan information using the so-called Map Filtering (MF) technique. The incorporation of MF allows the BPF to exploit long-range geometrical constraints.

This paper evaluates BPF with indoor localization based on WLAN RSSI fingerprinting. The filtering schema is evaluated using the propagation simulation in an office building, a typical environment for fingerprinting technique. Favorable result are obtained, showing positioning performance (1.34 m mean 2D error) superior to the PF-only no MF case (1.82 m mean 2D error), or up to 25% improvement. It is also shown that the performance is far better than the position estimates from conventional Nearest-Neighbour (NN) and Kalman Filter (KF) approaches using the same RSSI measurements.

Categories and Subject Descriptors

G.3 [**Probability and Statistics**]: [Probabilistic algorithms]

General Terms

Experimentation

Keywords

indoor localization, backtracking particle filter

1. INTRODUCTION

The Global Positioning System (GPS) has emerged as mainstream technology for outdoor localization. However, since GPS signals are heavily attenuated and reflected by building structures, the system does not provide sufficient availability or accuracy indoor. Several technologies have been proposed for indoor localization, such as UWB, infra-red sensors, inertial sensors (e.g. PDR), wireless sensor nodes (WSN) and wireless LAN (WLAN) [7].

The ubiquity of WLAN infrastructure makes this technology an attractive base on which to build indoor localization systems. The advantage of WLAN is that the technology provides a wireless communication infrastructure and RSSI measurements from the transceivers can readily be used for indoor localization.

Particle Filtering (PF) has been a prominent filtering schema for indoor RSSI-based localization. The non-linearity and non-gaussian nature of RSSI measurements make the PF technique well-adapted for estimating the user position. Several variants of the PF within a generic framework of the Sequential Importance Sampling (SIS) algorithm are widely used. These are often combined with a technique called Map Filtering (MF) which can take advantage of building plans information. Previous research showed that WLAN/RSSI-based indoor localization provides interesting results [1]. The typical room-level accuracy may be sufficient for some application domains. However, if the accuracy and resolution can still be improved, a larger number of application domains could be served.

The aim of this paper is to propose a novel variant of the Particle Filter, called the Backtracking Particle Filter (BPF). BPF is a technique for refining state estimates based on exclusion of invalid particle trajectories. In a previous publication [10], the authors described a framework for fusing building plans and PDR motion measurements with BPF filter. It was shown that the BPF can take advantage of long-range (geometrical) constraint information provided by various levels of building plan detail and provide high-accuracy position estimates in many instances.

In this paper, we evaluate the BPF framework with pattern matching localization technique based on RSSI fingerprinting. With this pattern matching technique, the BPF can take advantage of long-term likelihood sequences and can also use building plan information if MF is used.

The remainder of the paper is organized as follow. In Section 2, a pattern matching based positioning system is briefly introduced. The filtering algorithm and the novel Backtracking Particle Filter will be proposed in the Section 3. Section 4 will briefly describe the tools and simulation conducted. Section 5 will present the results of the experiments. Finally section 6 will conclude the paper.

2. INDOOR LOCALIZATION

The pattern matching indoor location system generally works in two phases. First, there is a calibration phase and the creation of a database of RSSI values, also known as fingerprints. The RSSI fingerprints are tuples consisting of an access point (AP) MAC address, a measured RSSI value and a position. A tuple is created for every available AP at the measurement position. Secondly, during the online tracking, the client's mobile device will scan for all available WLAN access points and measure their RSSI values. The RSSI data in turn is input to the PF estimator to estimate user position.

The calibration phase can be conducted manually by measuring RSSI at every grid point in the floor plan. While this calibration approach is accurate, it is expensive and time consuming. Re-calibration will be needed if there is a major change in the propagation environment, such as the relocation or addition of walls, furniture, or APs.

To overcome this problem, indoor propagation models can be used to predict the fingerprints, either entirely in simulation [11] using theoretical models, or alternatively using a hybrid predict/fit approach with small number of sampled fingerprints, propagation models and some data fitting algorithm [4].

There are two conventional approaches to the propagation modeling: empirical and deterministic. The advantages of empirical approaches are speed, simplicity of the input data (only a simple building plan is required) and straightforward prediction formulae. The main disadvantages are poor site-specific accuracy and the impossibility of predicting wide-band communication channel parameters. In contrast, deterministic models can be more accurate but they are considerably more complicated to implement [6].

In this paper, we use a simple empirical approach called the Multi-Wall Model (MWM) for fingerprint prediction [11]. In the MWM, the signal loss is given with following equation [9]:

$$L_{MWM} = L_1 + 20\,log(d) + n_W * L_W + n_F * L_F \qquad (1)$$

where L_{MWM} denotes the predicted signal loss, L_1 is the free space loss at a distance of 1m from the transmitter, d is the distance from the transmitter to the receiver, L_{Wall} is the contribution of each of n_W walls to the total signal loss, L_{Floor} is the contribution of each of n_F floors to total signal loss.
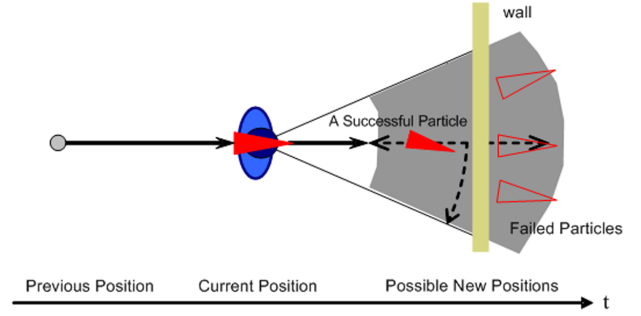

Figure 1: Particle Transition Near Obstacles: If a particle tries to move across walls or other obstacles defined in the map, it will be killed off.

3. FILTERING ALGORITHM

Particle Filtering (PF) is a technique that implements a recursive Bayesian filter using the Sequential Monte-Carlo method [2]. It is particularly good for dealing with non-linear and non-Gaussian estimation problems. It is based on a set of random samples with weights, called particles, for representing a probability density. The Particle Filter directly estimates the posterior probability density function (pdf) of the state using the following equation [8]:

$$p(\mathbf{x}_t|\mathbf{Z}_t) \approx \sum_{i=1}^{N} w_t \delta(\mathbf{x}_t - \mathbf{x}_t^i) \qquad (2)$$

where $\mathbf{x}_t^i$ is the i-th sampling point or particle of the posterior probability and w_t^i is the weight of the particle.

For indoor positioning, building plans are very useful information that can be used to enhance location accuracy and reduce uncertainty of walking trajectories. Particle Filters can take into account building plan information during the indoor positioning process with a technique called Map Filtering [5]. Map Filtering implements a fairly straightforward idea. New particles should not move to impossible positions given the map constraints. For example, particles are not allowed to cross directly through walls. Particle that transition through such obstacles are downweighted or deleted from the set of particles, as seen in Figure 1.

3.1 Particle Filter Implementation

During the prediction stage, each particle will have dynamics according to a motion model that represents the estimated object. Particles state can be modeled with:

$$\mathbf{x}_t^i = \left[\begin{array}{c} x_t^i \\ y_t^i \end{array} \right] = \left[\begin{array}{c} x_{t-1}^i + v_t^i cos(\alpha_t^i)\Delta t + n_{t-1} \\ y_{t-1}^i + v_t^i sin(\alpha_t^i)\Delta t + n_{t-1} \end{array} \right] \qquad (3)$$

Where v_t denotes velocity; α_t describes particle heading at the time t; n_{t-1} is a noise with Gaussian distribution.

In some applications, estimates of both the particle velocity and heading can be obtained directly from an inertial sensor measurement. In the absence of these measurements, the particle velocity and heading are modeled through *a heuristic approach*. The particle velocity is given by following equations:

$$v = [0, 10ms^{-1}]; v_t = |N(v_{t-1}, 1ms^{-2}\Delta t)| \qquad (4)$$

Particle heading is given by:

$$\alpha = [0, 2\pi]; \alpha_t = N(\alpha_{t-1}, 2\pi - \arctan(\frac{\sqrt{v_t}}{2})\Delta t) \qquad (5)$$

The inclusion of v_t in particle heading is to limit heading variation based on particle speed (people tend to slow down when he/she want to change direction of walk).

The new particle position, which is determined by the motion model, should not cross walls or other obstacles. If several crossing attempts fail, the particle will be categorized as invalid and the particle weight will also be changed according to the following rule:

$$w_t^i = \begin{cases} 0, & crossing\ wall\ particle \\ w_{t-1}^i\ p(\mathbf{z}_t|\mathbf{x}_t^i), & otherwise \end{cases} \qquad (6)$$

where $p(\mathbf{z}_t|\mathbf{x}_t^i)$ is the likelihood function. In the case of pattern matching localization, the likelihood function $p(\mathbf{z}_t|\mathbf{x}_t^i)$ describes the probability of receiving a set of signal level tuples (signature) in a specific location. Example on Likelihood function $p(\mathbf{z}_t|\mathbf{x}_t^i)$ formula is as follow [3]:

$$p(\mathbf{z}_t|\mathbf{x}_t^i) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(X_{z_t} - X_{x_t^i})^2}{2\sigma^2}\right] \qquad (7)$$

with X_{z_t} being the position returned by the database, $X_{x_t^i}$ the position of the ith particle at time step t, and σ the measurement standard deviation. X_{z_t} can be determined from NN algorithm, which calculate minimum signature distance (the minimum signal space distance between RSSI measurement and RSSI in fingerprint database) [1]:

$$d^* = argmin(\sum |T_d - T_z|) \qquad (8)$$

where d^* being the minimum signature distance, T_d is a tuple from the database and T_z is a tuple from received RSSI measurement. Figure 2 shows typical likelihood function of RSSI measurement of an access point in open space.
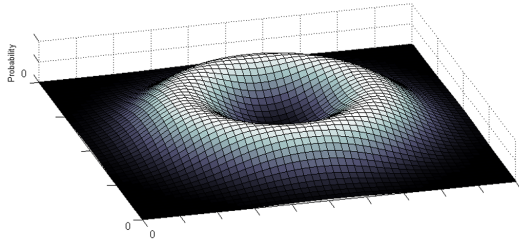

Figure 2: Typical likelihood function of RSSI measurement in open space, an access point is placed in the middle of the horizontal plane

3.2 Backtracking Particle Filter

Backtracking Particle Filter is a technique for refining state estimates based on particle trajectory histories. The incorporation of the Map Filtering technique allows the BPF to exploit the long-range geometrical constraints of a building plan and long-term likelihood function weighting. If some particles x_t^i are not valid at some time t, the previous state estimates back to x_{t-k} can be refined by removing the invalid particle trajectories. This is based on assumption that

an invalid particle is the result of a particle that follows an invalid trajectory or path. Therefore, recalculation of the previous state estimation $\hat{x}_{t-k}$ without invalid trajectories will produce better estimates. In order to enable backtracking, each particle has to remember its state history or trajectory.
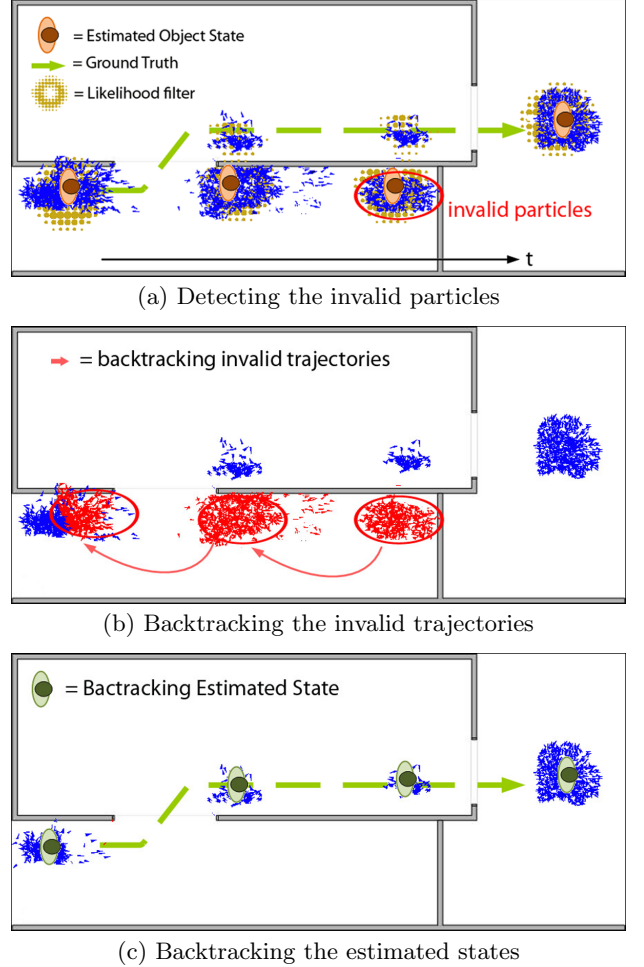

(a) Detecting the invalid particles

(b) Backtracking the invalid trajectories

(c) Backtracking the estimated states

Figure 3: BPF for pattern matching localization

The BPF implementation for pattern matching localization is illustrated in the following figures. Figure 3(a) shows a typical phenomenon when a standard Particle Filter is used for pattern matching indoor localization. It illustrates posterior density of particles in four time steps. The position estimates and the ground truth are shown in the image as well.

Map Filtering and the likelihood function categorize some particles as invalid between the 3rd and 4th step and the invalid particles are not subsequently resampled. Figure 3(b) shows how the Backtracking Particle Filter removes the invalid trajectories. Figure 3(c) illustrates the recalculated state estimates after backtracking. It can be seen that under certain conditions backtracking can improve state estimates relative to a normal PF.

The pseudocode below describes the complete BPF algorithm for state refinement.

BACKTRACKING-PF($N, tail$)

```
 1   sampling N particles from initial pdf
 2   tailcount ← 0
 3   repeat
 4           get z_t
 5           for i ← 1 to N
 6               do get x_i^t from p(x_t|x_{t-1})
 7                   calculate w̃_t^i = p(z_t|x_t^i)
 8           for i ← 1 to N
 9               do normalize w_t^i = w̃_t^i / ∑_{i=1}^N w̃_t^i
10           resample and inherit state history
11           estimate state x̃_t = (1/N) ∑_{i=1}^N x_t^i
12           if tailcount ≥ tail
13               then x̃_{t-tail} = (1/N) ∑_{i=1}^N x_{t-tail}^i
14           increment tailcount
15           increment t
16       until stop
```

The main features of the BPF for pattern matching localization can be seen in steps 6,10, and 13 of the pseudocode. During *prediction sampling* in step 6, a new particle is sampled from the transition pdf $p(x_t|x_{t-1})$ with the Map Filtering technique. In step 10, the resampling is followed by the inheritance of the state history. The resampling algorithm is taken from [8]. The inheritance step made the newly sampled particle x_t^{i*} will inherit its parent state (position and heading) $X_{t-1}^i \triangleq \{x_i, i = 1, 2, 3, ...t - 1\}$. This inheritance step will enable the backtracking of invalid trajectories and also the calculation of the backtracking state (step 13).

4. TOOLS AND SIMULATION
Simulations were run using the floor plan of a small, one storey office building, measuring approximately 50m x 50m (2,500m^2). The fingerprint database, i.e RSSI measurements for the entire simulation area, was estimated using the MWM. A ground truth path, approximately 150 meters in length was drawn on the floor plan through the office corridors, rooms and outdoor area. A nominal walking behavior was generated by advancing the current location of a simulated user along a ground truth path at a rate of 1 m/s at each simulation time step (1 second).

Noisy RSSI scan measurements were generated for each simulation time step by adding Gaussian noise with standard deviation of 5 dBm to the nominal, noise-free RSSI values for current position from fingerprint DB. The simulated RSSI values were then used as input to a probabilistic position estimating routines, which was then used as input to the PF and BPF applications, both of which were implemented in C++. One thousand particles were used during the filtering. For comparison purposes, position estimates were also calculated using the same noisy, simulated RSSI values with conventional nearest neighbour and Kalman filter approaches.

5. RESULTS AND ANALYSIS
As was to be expected, the conventional nearest-neighbour estimation method shows a large position scatter all along the simulated path. The primary reason for this relatively poor performance is that it is a memory-less algorithm and consequently cannot filter out any noise in the estimates. The Kalman filter, which try to refine NN estimation, has better trajectory. It can filter out noise in successive measurements, and can incorporate a motion model. See Figure 4(a) and Table 1 for details.

The BPF that can take advantage of long-term likelihood function and long-range (geometrical) constraint information yields excellent positioning performance (1.34 m mean 2D error), it shows enhancement up to 25% compare to PF only (1.82 m mean 2D error) and more than 3 times better compare to NN performance. More significantly, the BPF without MF yields improved positioning performance (1.62 m mean 2D error) compare to a PF-only (1.82 m mean 2D error). This result confirms that BPF can be performed via the elimination of trajectory errors based on likelihood function. The positioning accuracy is summarized in Table 1.

Table 1: Positioning Accuracy

	NN	KF	PF	BPF
without MF	μ =4.37	μ =3.57	μ =1.82	μ =1.62
	σ =4.66	σ =2.90	σ =1.50	σ =0.97
with MF	-	-	μ =1.67	μ =1.34
			σ =1.40	σ =0.80

The trajectory evolution over time is shown in 4(b) for estimation without MF. It can be seen that PF trajectory is more jagged than BPF. Trajectories of filtering with MF 4(c) are better since they are constrained by the building walls.

The tail value of the BPF is established empirically. The value is optimized by considering several parameters, most notably building plans dimension and trial duration. The simulation is performed with the tail value of 5 and below. While using bigger tail values are possible as shown in [10], smaller tail has more practical significance for real-time localization.

6. CONCLUSION
In this paper a novel Backtracking Particle Filter algorithm is proposed. The filter is evaluated with pattern matching localization.

It has been shown that BPF with building constraint information yields excellent positioning performance (1.34 m mean 2D error). It shows enhancement up to 25% compare to PF only (1.82 m mean 2D error). More significantly, the BPF without MF yields improved positioning performance (1.62 m mean 2D error) relative to a PF-only. This result show that BPF can be performed via the elimination of trajectory error based on likelihood function.
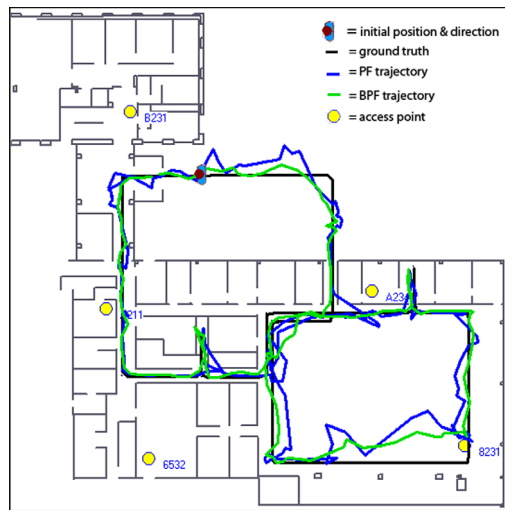
It is expected that this performance can be reproduced for many other environment and data encountered during indoor localization. Further experiments will be performed in the future to test this hypothesis.

(a) Trajectory of Nearest-Neighbour and Kalman Filter
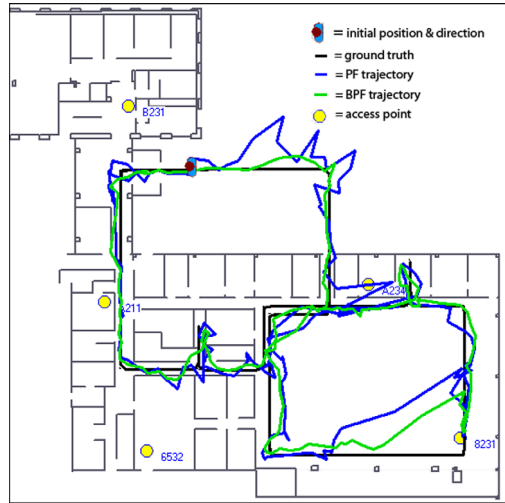
(b) PF and BPF Trajectory without Map Filtering

(c) PF and BPF Trajectory with Map Filtering

Figure 4: Trajectory for different methods

7. ACKNOWLEDGMENT

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