A Bayesian Approach for RF-Based Indoor Localisation

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Abstract—The proliferation of Wireless LAN and Wireless Sensor Network make the technologies become an attractive proposition for indoor localisation. Both technologies have provided communication infrastructure and hence RF-based localisation with WLAN and WSN becomes a software-only solution. WLAN-based localisation generally provides room accuracy, therefore sensor data fusion with WSN is proposed when better location accuracy is needed.

This paper will describe a Bayesian approach for indoor localisation. A suboptimal sequential Bayesian method of Particle Filter combined with Map Filtering technique is used for sensor data fusion between WLAN and WSN. The location system performance also will be evaluated.

I. INTRODUCTION

The proliferation of mobile computing devices has set forth a growing-interest in mobile positioning system. Mobile positioning has become increasingly interesting system most notably for context-aware application and emergency services. GPS has been the mainstream technology for location and tracking for outdoor environments. However, the received GPS signal in an indoor environment is too faint to provide sufficient accuracy. Therefore a number of systems have been proposed for indoor localisation based on ultrasound, infrared, and radio frequency [1].

The ubiquity of Wireless LAN (WLAN) infrastructure makes this technology an attractive proposition for location and tracking and it is also affordable for most organisations. Several experimental [4, 5, 6] and commercial WLAN-based tracking systems [7, 8] already exist

Apart from WLAN technology, the proliferation of wireless sensor networks (WSN) also opens a possibility for use in people location and tracking. The advantage of WLAN and WSN is that both technologies have provided a wireless communication infrastructure and hence RF-based location with WLAN/WSN becomes a software-only solution.

The main contribution of this paper is two fold. Firstly, we describe the implementation and evaluation of an indoor localisation system based on WLAN and WSN. Secondly, we present an analysis of our algorithms using Particle Filter and Map filtering.

II. INDOOR LOCALISATION

The location system works in two phases (see figure 1): firstly, the calibration, building a database of received signal strength indication (RSSI) or fingerprint. Secondly, the online tracking, the client’s mobile device will scan the RSSI from available WLAN access points and WSN.

During the calibration phase, the RSSI fingerprint is saved in a database in a form of signatures tuples (consisting of the access point MAC address and RSSI values).

III. ALGORITHM

A. Sensor Data Fusion

In order to taking advantage of data from various sensors and environment description, sensor data fusion framework is developed. Figure 2 show block diagram of WLAN, wireless sensor network and navigation sensor data fusion.
Since WLAN and WSN is measured with different frequency, they need to be synchronized before further processed in the tracking algorithm. WLAN and WSN measurement result are fused to the Particle Filter algorithm in a form of signature tuples of MAC-address and RSSI value. RSSI filter is used to smooth brief signal fluctuation of WSN measurement.

The Particle Filter motion-model is used to fuse navigational sensor data since the particle state, in addition to position, can consist of speed, acceleration and orientation. The Particle Filter takes advantage of environment description with map filtering technique. The map filtering technique lays in a principle of limiting the particles movement in a determined environment.

B. Sequential Bayesian Estimation

To define the problem during location estimation, the target state evolves according to the following discrete-time stochastic model:

\[ x_t = f_{t-1}(x_{t-1}) + n_{t-1}. \] (1)

Where \( x_t \) denotes the state of the target being estimated; \( f_{t-1} \) is a known, possibly non-linear function of the state \( x_{t-1} \); \( n_{t-1} \) is an independent and identically-distributed noise.

The measurement \( z_t \) is related to the target state with the following model:

\[ z_t = h_t(x_t) + e_t. \] (2)

Where \( h_t \) is a known, possibly non-linear function; \( e_t \) denotes an independent and identically-distributed noise. In the case of indoor localisation, it aims to filter the object state \( x_t \) based on the sequence of all available RSSI measurements \( Z_t = \{z_i, i = 1, \ldots, T\} \) up to time \( t \).

From a Bayesian perspective, the problem is to recursively construct the posterior pdf \( p(x_t | Z_t) \) given the data \( Z_t \) hence the name sequential Bayesian Estimation. In principle pdf \( p(x_t | Z_t) \) can be calculated in two stages: prediction and updates [2].

The prediction stages involve using the state model (1) via the Chapman-Kolmogrov equation:

\[ p(x_t | Z_{t-1}) = \int p(x_t | x_{t-1}) p(x_{t-1} | Z_{t-1}) dx_{t-1}. \] (3)

At time step \( k \) when measurement \( z_k \) becomes available, the updates stage is conducted using Bayes Rule:

\[ p(x_t | Z_t) = \frac{p(z_t | x_t, Z_{t-1}) p(x_t | Z_{t-1})}{p(z_t | Z_{t-1})}. \] (4)

With the normalizing constant:

\[ p(z_t | Z_{t-1}) = \int p(z_t | x_t) p(x_t | Z_{t-1}) dx_t. \] (5)

In the update stage (4), the measurement \( z_k \) is used to update the prior density to obtain the posterior density of the current state. Knowledge of posterior density enables an estimation to be made, for instance to obtain minimum-mean-squared-error (MMSE) of \( x_t \):

\[ \hat{x}_t^{\text{MMSE}} = \int x_t p(x_t | Z_t) dx_t. \] (6)

The aforementioned equations in reality are often hard or impossible to solve analytically. Especially when the measurement equation is non-linear or the noise distribution is non-Gaussian. Only in a special case where the equation is linear and the noise is Gaussian, an optimal solution does exist, such as the Kalman Filter and grid-based filters [2].

Since an indoor environment introduces complex multi-path propagation conditions, an RSSI-based tracking system is non-linear, non-Gaussian and provides fundamentally noisy measurements, which precludes an analytical solution. One has to use approximation or suboptimal filtering technique to solve the estimation problem. A number of sub-optimal solutions have been presented in [2] and [3]. This paper will focus on a sub-optimal non-linear filter approach called sequential Monte Carlo method or particle filter.

C. Particle Filter Implementation

Particle Filter is a technique that implements a recursive Bayesian Filtering using the Sequential Monte Carlo Method. It is based on set of random samples with weight, or particles, to represent probability density.

In the case of the considered indoor localisation, the Particle Filter gives a numerical approximation to equation (3), (4), (5), and (6) with the following algorithm.

**Algorithm 1: Particle Filter**

1. Initialisation: set \( t = 0 \), generate the initial set of \( N \) particles (state samples) from initial density and give them an equal weight. Generate:

\[ \{x_0^i\}_{i=1}^N \sim p(x_0), \quad w_0^i = \frac{1}{N}. \]
2. Prediction: determine a new position of each particle with the motion model and with a different noise realisation
\[ x'_i = f(x_i) + n_{i-1}, \quad i = 1, \ldots, N. \]

3. Update: update the weights with the likelihood function
\[ w'_i = w_i \cdot p(z_i | x'_i). \]
and normalise:
\[ \bar{w}'_i = \frac{w'_i}{\sum_{j=1}^{N} w'_j}, \quad i = 1, \ldots, N. \]

4. Resample: generate a new set of particles \( \{x'_i\}_{i=1}^{N} \) by resampling with replacement \( N \) times from \( \{x'_i\}_{i=1}^{N} \) with probability \( \Pr\{x'_i = x'_j\} = \bar{w}'_i \).

5. State estimation: determine the state estimation by
\[ x_i = \frac{1}{N} \sum_{i=1}^{N} x'_i. \]

6. Set \( t = t + 1 \) and go to step 2

D. Motion Model

During the prediction stage each particle will have dynamicity according to a motion model that represents the estimated object. Let \( x'_i \) denote the state vector that describes the particle position in local Cartesian coordinate. Particles motion can be modelled with:
\[ \begin{bmatrix} x'_i \\ y'_i \\ \alpha_i \\ v_i \end{bmatrix} = \begin{bmatrix} x'_{i-1} + v_i \Delta t \cos(\alpha_i) + n_{i-1} \\ y'_{i-1} + v_i \Delta t \sin(\alpha_i) + n_{i-1} \\ \alpha_i \\ v_i \end{bmatrix}, \]

Where \( v_i \) denotes velocity; \( \alpha_i \) describes particle direction at the time \( t \); \( n_{i-1} \) is a noise with Gaussian distribution.

Both particles velocity and direction can be obtained directly from an inertial sensor measurement. Nevertheless, inertial sensor is used only for direction measurement in this current experiment. Meanwhile, particle velocity is modelled through a heuristic approach.

The particle velocity is given by following equations:
\[ v = [0,10 \text{ms}^{-1}]; \quad v_i = \left| N(v_{i-1}, 1 \text{ms}^{-2} \Delta t) \right|. \]

In the absence of inertial sensor measurements, heading is given by:
\[ \alpha = [0,2\pi]; \quad \alpha_i = N(\alpha_{i-1}, 2\pi - \arctan(\frac{v_i}{2}) \Delta t). \]

E. Map Filtering

The particle movement is also taking into account environment description, i.e.: wall, room and corridor. Map filtering is implemented in a way that particles, which act as a people representation, can not move across a wall or another solid object. Particles are only permitted to move in corridors or within rooms.

Map filtering is implemented in a fairly straightforward way. The new particle position, determined by the motion model, should fulfil the requirements mentioned above. If an attempt to find a new position fails (when moving particle path is obstructed), the algorithm will try to find a new particle position according to the motion model (7), as seen in Figure 3. If several attempts within predetermined threshold still fail, the particle will die.

![Fig. 3  A particle can not move across a wall and try to find new position](image)

F. Likelihood Function

In the case of RSSI-based tracking, the likelihood function \( p(z_i | x'_i) \) describes the probability of receiving a set of signal level tuples (signature) in a specific location. Furthermore, it will be used for updating particle weight (as stated in algorithm 1, point 3).

The figures below show how likelihood function is used for updating the particle weight \( w_i \) and the posterior distribution subsequently. Figure 4 shows the posterior distribution at \( t = 0 \), the weights of the particles \( w'_0 = \frac{1}{N}, \quad N = 3000. \)

![Figure 4: Posterior distribution at t=0](image)

Fig. 4: From left to right: posterior distribution at \( t = 1, t = 20 \) and \( t = 30 \).

Blue circle represent likelihood function.
Figures 5 show when particles weight is updated with likelihood function (blue circle), resample to obtain posterior distribution and then state estimation is calculated at $t = 1, t = 20$ and $t = 30$.

IV. EXPERIMENT

The Department of Electronic Engineering (73m x 22m) at Cork Institute of Technology (CIT) was used as a test-bed to analyse the proposed system. The entire floor-plan was used for WLAN-based indoor localisation whereas WSN fusion is performed in part of the floor-plan where higher location granularity was perceived necessary. In this experiment, navigation sensor was used to provide heading measurement only.

WLAN and WSN infrastructure, which consists of 5 Orinoco AP-700 access points and 10 tmote nodes, was installed at the test-bed. Dell Latitude D505 laptop with internal Intel PRO/Wireless 2200 BG was used for both calibration and online tracking phase. Both access points and WLAN card were set in IEEE802.11g mode.

The first step was to draw floor-plan of the Electronic Engineering building. We have developed a tool for drawing the floor-plan in SVG (Scalable Vector Graphic) format. It is also possible to export the floor-plan from an AutoCAD file. Several tools have also been built using the C++ language. They include a site survey tool for the calibration phase (building the RSSI fingerprint), a tracking engine and TinyOS-based WSN software.

The RSSI fingerprint was built on top of the floor-plan that is divided into 1m square uniform-grid. Signal levels of WLAN access points and WSN were scanned every 1, 1/3 second respectively. Only a single floor problem was considered. Figure 6 illustrated WLAN fingerprint in CIT floor-plan.

A walk around the building was performed for the off-line indoor localisation. Some real measurements were collected along this path and then reused to measure the performances of each technique.

V. RESULT

Widely-used gauges of tracking accuracy are the mean error $\mu$ and standard deviation $\sigma$ of the difference between the ground-truth position and the prediction. The location accuracy in the test-bed is summarised in table 1, meanwhile the cumulative distribution function (CDF) of the error is shown in figure 7.

<table>
<thead>
<tr>
<th>LOCATION ACCURACY</th>
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<tbody>
<tr>
<td>WL</td>
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<tr>
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<tr>
<td>Particle Filter</td>
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<td>$\sigma = 1.38$</td>
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</tbody>
</table>

Table 1 shows that the Particle Filter algorithm provides reasonably good location accuracy. WLAN-based prediction ($\mu = 2.24$ with $\sigma = 1.37$) is considered sufficient to provide room containment information whereas WLAN and WSN fusion provide better accuracy ($\mu = 0.97$ with $\sigma = 0.53$).

The following figures depict the trajectory and error vector of the predicted location in the floor-plan. The vector origin shows the real user trajectory and the vector end point is the predicted location. A walk around building was performed from a room and a corridor for WLAN-based prediction. A walk between two rooms (b194 and b285) and corridor was conducted to evaluate WLAN and WSN sensor data fusion.
Figure 8 shows trajectory and error vector of WLAN-based prediction and figure 9 shows trajectory and error vector of WLAN&WSN fusion data. The Particle Filter produces good accuracy and small standard deviation. An accurate prediction is reflected in the small error vector for both predictions. A small standard deviation means that the algorithm gives smooth prediction which is further represented in the distinctness of the object trajectory.

VI. CONCLUSION

In this paper, our RF-based location system is summarised. A Bayesian approach for WLAN, WSN and navigation sensor data fusion is described. The Particle Filter algorithm with map filtering also evaluated.

It is found that the location system provide reliable prediction. WLAN-based prediction provides reasonably good accuracy whereas WLAN & WSN data fusion provide better granularity. It is recognised that WLAN and WSN fusion throughout the whole floor-plan is a possible scenario. However, the number of WSN that is needed will increase dramatically proportional to the floor size. Therefore more works still needed for investigating the trade-off between WSN density and location accuracy.

Future works include further use of navigation sensor with dead-reckoning technique and investigating propagation model for automatic fingerprinting.

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