RF-Based Location System in Harsh Environment

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Abstract. RF-based location tracking in industrial environment possesses many challenges due to the complex propagation condition. This paper will address some of the problems in this environment. Firstly, we evaluate the performance of RF-based tracking in a harsh environment, i.e. in a car manufacturing plant. Secondly, the research presents a comprehensive study of an algorithm that utilises Bayesian filters, leading to robust location and tracking estimation.
The evaluation of the location system was conducted in three test-beds. One test-bed mimics an office environment and the second and the third an assembly hall in car manufacturing plant.

Keywords: RF-based location, Particle Filter, Indoor Tracking

1 Introduction

The emergence of mobile computing devices and applications has fostered a growing-interest in location-aware systems and services. GPS has been the mainstream technology for location and tracking for outdoor environments. Since GPS does not provide enough accuracy in indoor environments, a number of systems have been developed based on RF, infra-red, ultrasound, or Ultra Wide Band (UWB) technologies [1] [2].

The ubiquity of WLAN infrastructure makes this technology an attractive proposition for location and tracking and it is also affordable for most organisations. Several experimental [8], [9], [10] and commercial WLAN-based tracking systems [3], [4] already exist. Apart from WLAN technology, the proliferation of wireless sensor networks (WSN) also opens a possibility of using them in people location and tracking.

The advantage of WLAN and WSN is that both technologies primarily provide a communication infrastructure and hence the WLAN/WSN location and tracking system becomes a software-only solution. This is especially appealing in industrial manufacturing environments where any extra infrastructure increases system maintenance cost and can also interfere with others electronic devices.

The main contribution of this paper is two fold. Firstly, describes the implementation and performance evaluation of a novel WLAN/WSN RF-based tracking system in a harsh environment, i.e. in an industrial environment. Secondly, presents an analysis of an algorithm utilising Bayesian filters leading to robust location and tracking estimation.

2 System Requirements

The location system was developed within the context of the EC FP6 IST WearIT@work project, which develops wearable computing technology for health care, industrial, maintenance, and fire fighting scenarios. The system analysis presented here targets operation under the following conditions found in a car manufacturing plant of Skoda, covering both the production and assembly hall and administrative buildings [5]. The production and assembly hall environment features:

- Large open indoor spaces
- Spaces with large metallic structures
- Electrical and magnetic interference from equipment and tools
- Complex multi-path propagation conditions

WLAN-based tracking systems work best in an environment which does not consist of large open spaces and metallic structures. Therefore, it is more suitable to be used in the administrative building. Furthermore, room containment estimation is considered sufficient in the administrative building.

In the production and assembly hall, where more challenging environment is exist and higher location granularity is required, WLAN-based tracking alone is considered not sufficient. The use of WSN technology will be beneficial for the location system. To satisfy these requirements, the following system architecture is proposed.

3 System Architectures

The tracking system operates in an environment where WLAN and WSN infrastructure is installed and is based on client-server architecture as seen in Figure 1.

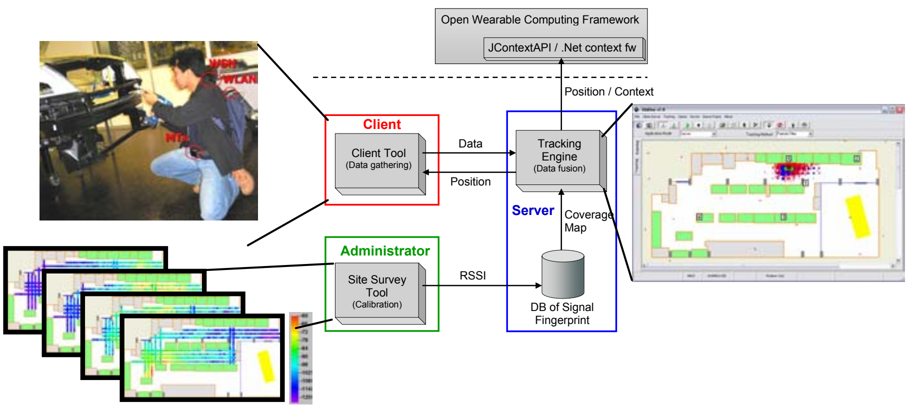

Fig. 1. The architecture of RF-based location system

The users (client side) will carry WLAN-enabled mobile nodes, which have WSN device attached. The server side hosts the location engine software, which receives data from clients and performs the location prediction.

The user location and tracking system operates in two phases: Firstly, building a database of the received signal strength indication (RSSI fingerprint). Administrator tool will be used during this phase. The RSSI fingerprint is saved in database in a form of *tuples* (consists of MAC address of an access point and values of RSSI).

Secondly, the online tracking, the users' mobile device will scan the RSSI from the available access points and wireless sensor nodes and send them to the algorithm to estimate user location.

4 Tracking Algorithm

The location system is implemented with a Recursive Bayesian algorithm. In order to take advantage of environment description, the algorithm will be combined with Map Filtering technique.

4.1 Recursive Bayesian Estimation

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

$$x_t = f_{t-1}(x_{t-1}) + n_{t-1} \ . \tag{1}$$

Where x_t denote the state of 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:

$$z_t = h_t(x_t) + e_t \, . \tag{2}$$

Where h_t is a known, possibly non-linear function; e_t denotes an independent and identically-distributed noise. In the case of people tracking, we are interested to filter people state x_t based on a sequence of all available RSSI measurement $Z_t \triangleq \{z_i, i = 1, \ldots t\}$ up to time t.

From a Bayesian perspective, the problem is to recursively quantify the state x_t at time t, taking different values, given the data Z_t up to time t. Therefore, it is required to construct the posterior pdf $p(x_t \mid Z_t)$. In principle, pdf $p(x_t \mid Z_t)$ can be calculated in two stages: prediction and updates [6].

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

$$p(x_t \mid Z_{t-1}) = \int p(x_t \mid x_{t-1}) p(x_{t-1} \mid Z_{t-1}) dx_{t-1} \ . \tag{3}$$

At time step k when measurement z_t becomes available, the updates stage is conducted using Bayes Rule:

$$\begin{aligned} p(x_t \mid Z_t) &= p(x_t \mid z_t, Z_{t-1}) \\ &= \frac{p(z_t \mid x_t Z_{t-1}) p(x_t \mid Z_{t-1})}{p(z_t \mid Z_{t-1})} \\ &= \frac{p(z_t \mid x_t) p(x_t \mid Z_{t-1})}{p(z_t \mid Z_{t-1})} \end{aligned} \tag{4}$$

With the normalizing constant:

$$p(z_t \mid Z_{t-1}) = \int p(z_t \mid x_t) p(x_t \mid Z_{t-1}) dx_t \ . \tag{5}$$

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

$$\hat{x}_t^{MMSE} = \int x_t p(x_t \mid Z_t) dx_t \ . \tag{6}$$

The aforementioned equations 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 when the equation is linear and the noise is Gaussian an optimal solution does exist, such as Kalman Filter and grid-based filters [6].

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. A number of sub-optimal solutions have been presented in [6] and [7]. This paper will focus on a sub-optimal non-linear filter approach called sequential Monte Carlo method or Particle Filter.

4.2 Particle Filter Implementation

Target tracking using Particle Filter methods has a long history in the research literature [11], [12], [13], [14], [15], [16]. Particle Filter is a technique that implements a recursive Bayesian Filtering by the Sequential Monte Carlo Method. It is based on a set of random samples with weight, or particles, for representing probability density. The main idea is to compute the posterior probability from a set of particles and its associate weight.

In case of the considered people tracking, Particle Filter gives a numerical approximation to equation (3), (4), (5), (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:

$$\{x_0^i\}_{i=1}^N \sim p_{x0},\ w_0^i = \frac{1}{N} \quad .$$

2. *Prediction:* determine new position of each particles with the motion model and with different noise realization

$$x_t^i = f(x_{t-1}) + n_{t-1},\ i = 1,...,N \ .$$

3. *Update:* update the weights by the likelihood function

$$w_t^i = w_{t-1}^i\, p(z_t \mid x_t^i) \ .$$

and normalize:

$$\overline{w}_t^i = \frac{w_t^i}{\sum_{j=1}^N w_t^j}$$

$$i = 1,...,N$$

4. *Resample:* Generate a new set of particles $\{x_t^i\}_{i=1}^N$ by resampling with replacement N times from $\{x_t^j\}_{j=1}^N$ with probability $\Pr\{x_t^i = x_t^j\} = \overline{w}_t^j$

5. *State estimation:* determine state estimation by

$$x_t = \frac{1}{N}\sum_{i=1}^N x_t^i \ .$$

6. Set $t = t + 1$ and go to step 2

4.3 Motion Model

During the prediction stage each particle will have dynamicity according to a motion model that represents the estimated object. Let x_t^i denote the state vector that describes position of the particle in local Cartesian coordinate. The motion of the the particles can be modelled with:

$$x_t^i = \begin{pmatrix} \mathrm{x}_{t-1}^i + v_t \triangle t \cos(\alpha_t) + n_{t-1} \\ \mathrm{y}_{t-1}^i + v_t \triangle t \sin(\alpha_t) + n_{t-1} \end{pmatrix} . \tag{7}$$

Where v_t denotes velocity; α_t describes particle direction at the time t; n_{t-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:

$$v = [0, 10ms^{-1}]; \qquad v_t = | N(v_{t-1}, 1ms^{-2} \triangle t) | . \tag{8}$$

In the absence of inertial sensor measurement, heading is given by:

$$\alpha = [0, 2\pi]; \qquad \alpha_t = N(\alpha_{t-1}, 2\pi - \mathrm{atan}(\frac{\sqrt{v_t}}{2}) \triangle t) . \tag{9}$$

4.4 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 2. If several attempts within predetermined threshold still fail, the particle will die.

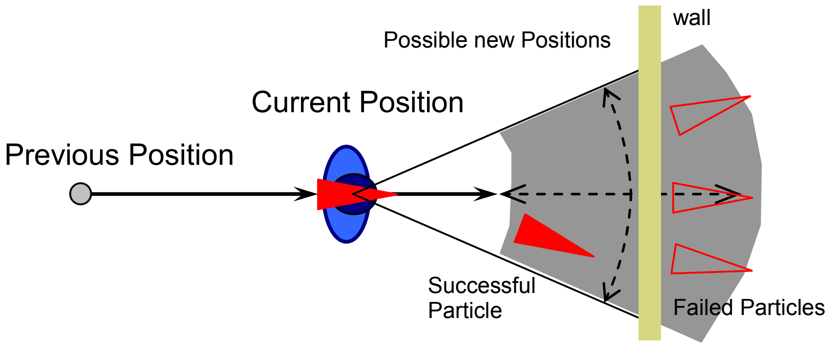

Fig. 2. A particle cannot move across the wall and try to find new position.

4.5 Likelihood Function

In the case of RSSI-based tracking, the likelihood function $p(z_t \mid x_t^i)$ 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_t and the posterior distribution subsequently. Figure 3 shows the posterior distribution at $t = 0$ and the weights of the particles $w_0^i = \dfrac{1}{N}$.

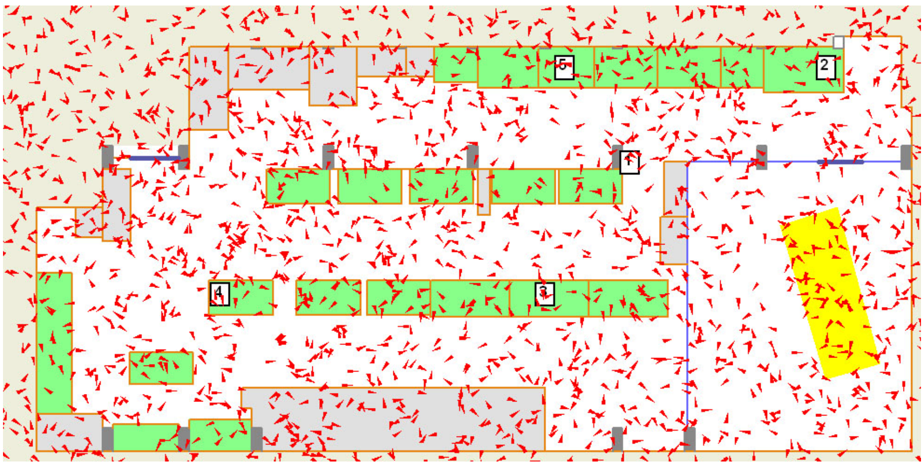

Fig. 3. Posterior distribution at $t = 0$

Figures 4 shows when particles weight is updated with likelihood function (blue circle), resampled to obtain posterior distribution and then state estimation is calculated at $t = 1, t = 20$ and $t = 30$.

Fig. 4. From left to right: posterior distribution at $t = 1, t = 20$ and $t = 30$. Blue circle represents the likelihood function

5 Experimental Setting

To analyse the proposed system, we use three experimental test-beds. The first test-bed was implemented in Department of Electronic Engineering building (1533 m^2) at Cork Institute of Technology (CIT) building. This test-bed has a WLAN infrastructure with 5 Orinoco AP-700 installed. The second and third test-bed, mimicking a car manufacturing plant, was implemented in a garage room and Power Electronic Laboratory at ETH, Zurich.

WLAN and WSN infrastructure was installed for the experiments in the garage room (5.5 x 7m). It consisted of 4 Orinoco AP-700 access points and 4 wireless sensor nodes (Zigbee nodes).

Power Electronic Laboratory (21 x 11m) had a wireless infrastructure, which consisted of 4 Orinoco AP-700 access points and 16 wireless sensor nodes (tmote nodes). The user carried a mobile device (Soekris embedded PC or tablet PC), which had a WLAN card and WSN client attached.

The RSSI fingerprint was built on top of the floor-plan that divided into uniform-grids. Signal levels of access points and WSN were scanned every 1 second. Only a single floor problem was considered. Figure 5 illustrated signal fingerprint in CIT floor-plan.

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

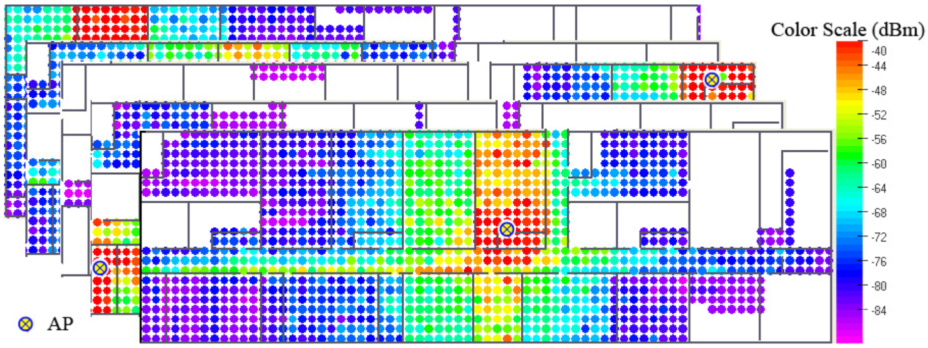

Fig.5. Visualisation of signal level fingerprint in an administration building test-bed

6 Results

Location accuracy is measured by calculating the mean error between a user real position and the estimated location in Cartesian coordinates. The performance of the location system in the three test-beds is summarised in Table 1.

Table 1. Location Accuracy

	Administration Building	Garage	Power Electronic
Location Accuracy	$\mu = 1.98$ $\sigma = 1.39$	$\mu = 1.18$ $\sigma = 0.81$	$\mu = 1.75$ $\sigma = 0.86$

It can be seen that the location system produce reasonably good accuracy for all the test-bed. In the administration building test-bed, the location system solely used WLAN technology. The location accuracy ($\mu = 1.98$ $\sigma = 1.39$) is considered sufficient for representing room containment.

On the other hand, we found that WLAN alone did not provide sufficient accuracy in the garage and Power Electronic test-bed since the signal level is relatively homogenous. Therefore, both WLAN and WSN were used. It is found that the fusion between WLAN and WSN provided good accuracy ($\mu = 1.18$ in the garage test-bed and $\mu = 1.75$ in the Power Electronic test-bed). Figure 6 shows the cumulative distribution function (CDF) of location accuracy in the three test-beds.

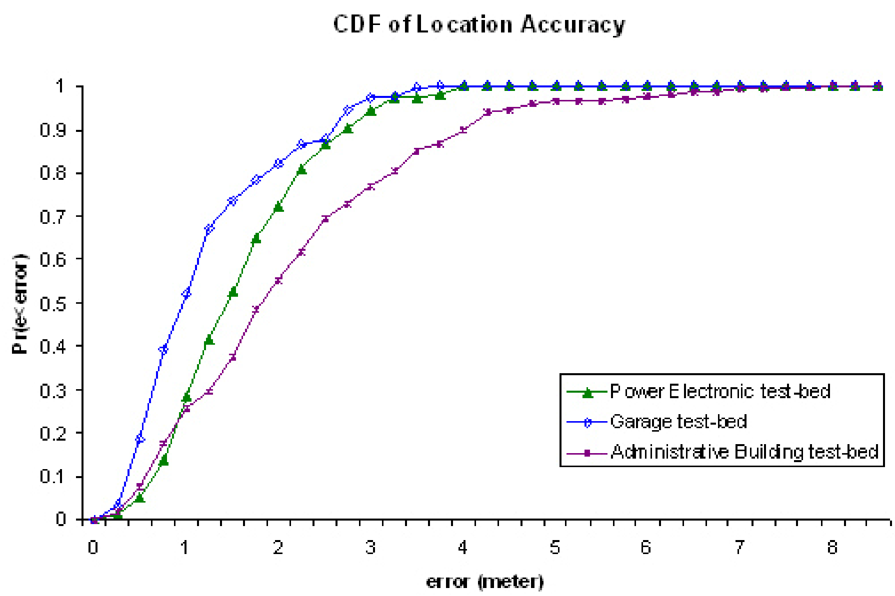

Fig.6. CDF of Location Accuracy with Particle Filter algorithm

6 Conclusions

The system performance using three experimental test-beds is summarised. The system performance shows favourable results. Particle Filter algorithm also works reasonably well for tracking in industrial environment. For administration building environment where room accuracy is sufficient, WLAN alone provide adequate accuracy. Meanwhile in industrial environment that also need more accurate estimation, the fusion between WLAN and WSN can provide reliable position estimation.

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