Indoor Localization and Tracking using Posterior State Distribution and Fingerprint Interpolation

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Abstract

Indoor localization is one of the essential modules in mobile wireless application. In this paper, the problem of location estimation and tracking of mobile user in a fixed wireless network is addressed. A strategy based on empirical map of received signal strength with interpolation to reduce the calibration effort for radio map creation is proposed. The proposed system models the motion dynamics of a mobile user as a hidden markov model in which each state corresponds to geo-location then tracking the user location using the posterior HMM state distribution. We present experimental results that demonstrate the ability of our tracking system to estimate the user location with a high degree of accuracy and less calibration effort.

Keywords: Localization and tracking, estimation theory, hidden markov model, wireless networks.

1. INTRODUCTION

Indoor Localization System (ILS) have become very popular in the recent years. The Indoor Localization System refers to the applications that rely on location detection as to detect a products stored in a warehouse, location detection of medical personnel or equipment in a hospital, location detection of fire-men in a building on fire [1], [14], detecting the police dogs location trained to find explosives in a building, searching for tagged maintenance tools scattered all over a plant, safety and healthcare [2].

The Global Positioning Systems (GPS) [3] are the most widely used tracking systems for civilian positioning service, and can offer accuracy close to 10 meters. However, GPS are outdoor only cannot provide good accuracy in indoor environments since the satellite signals are blocked by building obstructions. Many indoor localization system have been proposed such as Ultrasound [4], Infrared Ray [5], Radio Signal [6], Cellular network [7], Computer Vision [8], PHY information [9], Bluetooth technique [10]. Most of these systems are able to provide accurate results; however, they depend on additional hardware or large-scale infrastructures. Thus, such systems are hard to be widely deployed due to significant cost and energy consumption and specific environment range limitations [11].

The indoor Localization techniques rely on different kind of measurements that get relative position information between nodes as , among others, the angle of arrival (AoA) [12], [13],the time of arrival (the time that is taken by the radio signal to propagate from one node to another), the time difference of arrival (TDoA; the time interval between the reception of a radio signal and an ultra sound that is emitted by a beacon), and the RSS (an index of the received signal power). Approaches based on the first three quantities require specific devices such as array antennas for the AoA [15], ultra sound modules for TDoA, dedicated hardware and software to maintain node synchronization [17], or motion detection sensors such as magnetometers and IR motion sensors [3].

The ILS architecture consists of at least two separate hardware components: a signal transmitter (Access Point) and a measuring unit (Mobile Client). The latter usually carries the major part of the system computation. Most of the RSS indoor positioning system uses either a location detection by radio signal propagation models [16] or location fingerprinting techniques [15]. The enlargement of applicable areas is strangled by pretty limited fingerprint data of building interiors. The propagation model based methods will first calculate the distance between the nodes based on the signal propagation model, and then use lateration techniques positioning or maximum likelihood estimation method to figure out the position of the unknown nodes. However, fingerprinting techniques is divided into two phases: training and operating. In the training stage, a site survey process (calibration), in which engineers record the RSS fingerprints (e.g. WiFi signal strengths from multiple Access Points, APs) at every location of an interested area and accordingly build a fingerprint database (radio map) in which fingerprints are related with the locations where they are recorded. In the operating stage, when a mobile user sends a location query with his current RSS fingerprint, localization algorithms retrieve the fingerprint database and return the matched fingerprints as well as the corresponding locations [17].

The remainder of this paper is organized as follows. After a review of the related works (see Section II), in Section III, Data collection background is presented, in section IV, The problem is presented in a formal approach, and the steps for the design of a localization system are described in detail. Then, In Sections V, simulations and real-world experiments to assess and validate the proposed architecture and algorithms are presented, respectively.

Finally, in Section VI, some considerations on the results are drawn.
2. RELATED WORK

Our proposed approach belongs to RSS map-based localization systems and makes use of a Hidden Markov Model relying on empirical RSS measurements that are collected in the real environment or generated using propagation model, similarly to that proposed in [14]. Many researchers using HMM to model the localization problem as a classification problem. In [18] a LOCADIO localization system is designed that use two HMM which taking into account the node motion, building’s floor plan, expected pedestrian. In [19], a localization algorithm based on an HMM Bayesian approach that models the node moving capabilities and simulations shows that performances achieved by keeping into consideration mixed LOS/NLOS conditions for all radio links are similar to those obtained in an ideal LOS propagation environment. In [20] HMM is used on GSM networks and the localization errors depend on the grid cell length. Those papers all apply HMM into WSN localization, and achieve localization accuracy results up to the size of areas corresponding to classes. In [27], [28], [29] interpolation techniques for signal strength map are applied to gain a high precision but without using a tracking algorithm.

3. DATA COLLECTION

Received signal strength data processing in indoor positioning systems can be divided into two main groups. One group is based on wave propagation and relies on computing distances between mobile devices and points whose coordinates are known. These second group is based on mapping by combination of signal strength measurements and geographical coordinates, called a signal strength (SS) map.

3.1 Propagation Models

By using a mathematical model of indoor signal propagation, we can generate a set of theoretically computed signal strength data. The data points correspond to grid locations spaced uniformly on the network. The localization algorithm can then estimate the location of the mobile user by matching the signal strength measured at the mobile location with the theoretically computed signal strengths at these locations. It is clear that the performance of this approach is directly impacted by the “goodness” of the propagation model [21]. For a radio channel, signal propagation in an indoor environment is effected by reflections, diffraction, and scattering of radio waves caused by structures within the building. The transmitted signal generally reaches the receiver via multiple multipath causes’ fluctuations in the received signal envelope and phase, and the signal components arriving from indirect and direct paths combine to produce a distorted version of the transmitted signal. In general, indoor models may be classified by line-of-sight (LOS) or non line-of-sight (NLOS) [25], some of the key models are Partition Losses (same floor), Partition losses between floors, Log distance Path loss Model, Attenuation

3.2 Signal Strength Maps

Signal strength map systems are based on mapping by combination of geographical coordinates and signal strength values (RSSI). Geographical coordinates contain at least basic coordinates as Cartesian (x, y, z) coordinates. Two main steps are required to be identified in signal strength map-based systems: an offline training step builds a signal strength map by using the layout of the building test-bed and record the signal strength corresponding to its geo-location on the layout. Then, the online positioning step relies on the signal strength map previously built. For both steps, two approaches exist. The offline step is performed either by measurements or by simulation. The online step consists in matching a signal strength measurement to the signal strength map content. Matching can be either probabilistic or deterministic. Building a signal strength map by measurements implies moving physically to every location in the map and performs a measurement [1]. Whereas this method is simple to understand and use, and gives real measurements, it requires a lot of time. On the other hand, building the signal strength map by simulation requires a lot of work to build a propagation model used to compute the signal
strength map. Google released Google Map 6.0 that provides indoor localization and navigation available only at some selected airports and shopping malls in the US and Japan.

4. SYSTEM MODELING

The proposed model is divided into two phases: offline and online phases. During the offline phase, the RSS readings from the base station are collected by the mobile device at known locations, then an interpolation process will be applied using kernel regression to generate fingerprint database with a finer resolution. During the online phase, RSS measured by the moving user from all the base station are compared to the offline interpolated fingerprint database to estimate its current mobile location. The moving user dynamics are modeled as a markovian homogenous first order process and therefore allow the HMM to estimate and track the moving user position as shown in figure 2.

4.1 Received Signal Strength Map Modeling

The received signal strength distribution over the area of interest is built by measuring the RSS, $S$ over the links between the access points and the moving user which is sensed by the moving client. Without loss of generality, let $K$ be a two dimensional physical space to be the monitored indoor environment which is composed of $L$ access points (also called Anchors) is deployed over region $K$ at a fixed and known locations $\mathbf{L}_{R_0}=[L_{R_0}1, L_{R_0}2]\in K$ where each location represent one grid cell. As a matter of fact, the state $q_h$ is not a directly measurable quantity and thus it has to be computed from $L$ measurements that are exchanged at each time step between MC and APs, where each measurements $\mathbf{L}_{R_0}$ is the power (dBm) of the signal that is transmitted by the $L_{R_0}$ AP as received by the MC.

4.2 Fingerprint Interpolation

Signal strength maps are based on building a regular grid of tiles that map the measured signal strength to its geo-location. Direct measurement of RSS at each grid location fingerprint is expensive and requires a lot of labor effort; we use an interpolation process to build a finer grid that would be close enough to the observed one. We use an interpolation approach to build an interpolated signal strength map. Building interpolated signal map is similar to surface fitting between data points; our goal is to extend the position location $L_{R_0}$ into much finer grid $L_{R_0}$ using a certain small step. Linear interpolation is one of the most common used methods as in [26], which involve estimating a new data value by connecting every two fingerprint with a straight line. If the two known values are $L_{R_0}(X_1, Y_1)$ and $L_{R_0}(X_2, Y_2)$ then the interpolated value at the required position $L(X, Y)$ is:

$$L(X, Y) = u(L_{R_0}(X_1, Y_1)) + (1-u)(L_{R_0}(X_2, Y_2))$$

Where $u$ is a number from 0 to 1 that represent the fraction of the distance between $L_{R_0}(X_1, Y_1)$ and $L_{R_0}(X_2, Y_2)$ at which $L_{R_0}(X, Y)$ lies.
4.3 Localization by Hidden Markov Model

The moving client movement are modeled as a markovian first order process and therefore we use the Bayesian minimum mean square error (BMMSE) to estimate the moving client position x(t) based on a finite historical observation S. The term MMSE more specifically refers to estimation in a Bayesian setting with quadratic cost function. The basic idea behind the Bayesian approach to estimation stems from practical situations where we often have some prior information S about the parameter to be estimated.

\[
\bar{X}(t) = E[x(t)|x_{t-T+1},...,x_T] \quad (3)
\]

\[
\int_{x_{t-T+1}}^{x_{t}} X_{t} P(X_{t}|x_{t-T+1},...,x_{T}) dx_{t} \quad (4)
\]

Let us consider the prior information (RSS) S is a markovian process \( \lambda \) in which the position x(t) plays the role of the hidden state sequence and O denote the observation sequence at state q \( \{1,2,...,N\} \) where N is the number of grid cells and for more convenience \( \mathbb{Q}_{t}=S_{t-t-T+4}^T \) and \( \bar{X}(t) \) can be approximated as the following equation

\[
\bar{X}(t) = E_q\{x_q|x_{t-T+1},...,x_T,\lambda\} \quad (5)
\]

Where the expectation in (3) is taken with respect to the discrete variable \( q \), which corresponds to x(t) at grid location

\[
\bar{x}(t) = \sum_{q} x_q P(q|x_{t-T+1},...,x_T) \quad (6)
\]

So Mathematically,

\[
P(q_t = q|x_{t-T+1},...,x_T,\lambda) = \frac{P(q_t = q|x_{t-T+1},...,x_T,\lambda)}{P(q_t = q|x_{t-T+1},...,x_T)} \quad (7)
\]

Here \( P(q_{t-T+1},...,q_T,q_t = q|x_{t-T+1},...,x_T) \) is the forward variable in the HMM like the following equation

\[
\bar{X}(t) = \sum_{q} x_q P(q_{t-T+1},...,q_T|x_{t-T+1},...,x_T) \quad (8)
\]

A HMM model \( \lambda \) can be represented as \( \lambda = [\pi, A, B, q] \)

4.3.1 Hidden States

\( q = \{q_1,q_2,q_3,...,q_T\} \) is the set of all possible states (grid location)

4.3.2 Initial State Probability

\( \pi = P(q_1) \) if no a priori knowledge of the initial position is given we can simply impose a uniform initialization all over the states.

\[
\pi_q = \frac{1}{\text{# of states}} \quad (10)
\]

4.3.3 Transition Probabilities

Let the Moving client MC location qi be defined in the discrete finite set consisting of X1 X2 positions x=[x1, x2], with x1 X, x2 Y. The MC movement within the two dimension space at each time i is modeled as first order markov model:

\[
q_i = q_{i-1} + v_i \quad (11)
\]

Where \( v_i \) denote the random walk noise process as walking or running movement which can be expressed with a Gaussian pdf. The transition between states are governed by the X1*X2 probabilities \( A_{m,n} = P[q_i = n|q_{i-1} = m] \) for \( m=[x1_1,x2_1],n=[x1_2,x2_2] \) where the transition probability \( A_{m,n} \) is the probability for the MC to switch from state \( q_{t_i} \) to \( q_{t_i+1} \). In indoor environment which includes hallway, rooms and doors, the transition probability can be considered as a unit step probability corresponding to unit movement. Nodes can be considered to be connected by edges when they are reachable from each other in a single movement. States m and n represent adjacent nodes, so if two nodes are blocked by a wall so no edges exist between them so its probability will be zero.

4.3.4 Observation Probabilities B

The observation associated with a state is the RSS vector of the MC from APs. It is the probability of measuring \( \mathbb{Q}_{t_i} \) being the MC in the \( q_{t_i} \) a vector whose mean and variance are

\[
\mu = \begin{bmatrix}
O_{1}(q_{t_i}) \\
O_{2}(q_{t_i})
\end{bmatrix} \quad (12)
\]

\[
C(X_{t}) = \begin{bmatrix}
\sigma_{x1}^2(X_{t}) & 0 \\
0 & \sigma_{x2}^2(X_{t})
\end{bmatrix} \quad (13)
\]

The probability density function (pdf) of each measurement is

\[
P(O_{1,2}|q_{t_i}) = \frac{1}{2\pi\sigma_{x1}^{2}(q_{t_i})\sigma_{x2}^{2}(q_{t_i})} \exp\left(-\frac{(O_{1,2}-\mu)^2}{2\sigma_{x1}^{2}(q_{t_i})\sigma_{x2}^{2}(q_{t_i})}\right) \quad (14)
\]

4.4 Gaussian Distribution Moving Dynamics

The MN dynamics are assumed to be a 2 dimension random walk, which is modeled by a first order Markov process, i.e.

\[
X_{t+1} = X_{t} + W_t \quad (15)
\]

where \( X_t \) is the current position of the mobile user, \( X_{t-1} \) is the prior position and the modeled process is driven by a random Gaussian noise term \( W_t \) whose features are determined by some hypotheses on the node dynamics. The polar coordinates \( \rho = \sqrt{X_t^2 + X_{t-1}^2} \) and \( \theta = \arctan(X_t - X_{t-1})/(X_{t-1} - X_{t-1}) \), also assuming average walking and running speed of about, respectively, 1.3 and 4.4m/s [1]. At each time step, the steady condition is the most probable behavior, where as the probability of moving decreases with the traveled distance in any direction; the

Figure 5 Gaussian motion model probability distribution
standard deviation $\sigma$ is set to 3, which means that the majority of the MN movements are characterized by a velocity that is smaller than 3 m/s. Figure 3 are generated by mat-lab to simulate a moving client in a north-east direction with 1.3 standard deviation. In polar coordinates, this pdf can be expressed as

$$f_{\theta}(\theta) = \frac{1}{\pi\sigma} \sqrt{\frac{\sigma}{\pi \beta}} e^{-\frac{\sigma^2}{\pi \beta}}$$

$$f_{\rho}(\rho) = \frac{1}{2\pi}$$

5. SIMULATIONS AND DISCUSSIONS

The localization performance is evaluated by simulation using both radio wave propagation software simulator and real measurement test-bed. A signal strength map data of Faculty of Computer Science and Information Technology, Riga Technical University [14] is used to test our proposed model in an actual operative scenario.

5.1 Radio Wave Propagation Simulator

A 3-D ray-tracing based software package called the Radiowave Propagation Simulator (RPS Ver. 5.3) [30] is used in order to emulate the indoor propagations. RPS is able to generate a fine-resolution RSSI taking into consideration the effect of the penetrations, reflections, diffractions caused by an RF signal after the environment model, transmitter-receiver locations, antenna characteristics are specified by the user. RPS accuracy has been verified via a comparison with real indoor experimental measurements in [31]. We build a 3-D model experimental environment of industrial basement floor (see figure 6) as used in [1] about 1500 m² wide (37*41 m) and 3m ceiling high, on average. That environment is considered to be large and a critical because it is characterized by reinforced concrete pillars and walls (1.5 m wide). The anchor node position deployment is checked using the RPS to test the electromagnetic signal coverage of the whole environmental area as shown in figure 6. RPS simulator gives the ability to choose the propagation model used to calculate the signal strength for each location in the test-bed environment. As shown in figure 7 (a) the signal strength of AN2 is affected by the presence of the thick walls which is more realistic than figure 7 (b) that use path loss propagation model that neglect the presence of any obstacles present in the indoor environment.

Each anchor node is modeled as an isotropic source with 2.4 GHz frequency, 0 dBm transmission power and 2 m antenna height. The receiver nodes cover the whole area with 0.5 m grid size and 1.5 m height to receive the received signal strength of the signal from the anchor nodes. The same mobile pattern in [1] is built to evaluate and compare the position estimation accuracy with our proposed model as shown in figure 8.

**Figure 6** RPS simulated power distribution of the of industrial basement floor. The thicker lines correspond to armored concrete walls and pillars.

**Figure 7** Received signal strength distribution for AN 2(see figure 3). (a) Indoor multi-wall propagation model. (b) path loss propagation model.

**Figure 8** Examples of position estimation of the mobile node reference path (Solid line), discrete position estimation (Dots line).
### Table 1: Localization error results

<table>
<thead>
<tr>
<th>Method</th>
<th>Grid Spacing (m)</th>
<th>Estimation Error (m)</th>
<th>Complexity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bayesian Filtering</td>
<td>0.5</td>
<td>0.77</td>
<td>High</td>
</tr>
<tr>
<td>HMM</td>
<td>0.5</td>
<td>0.14</td>
<td>High</td>
</tr>
<tr>
<td>MLE</td>
<td>0.5</td>
<td>0.25</td>
<td>High</td>
</tr>
<tr>
<td>HMM</td>
<td>1.0</td>
<td>0.53</td>
<td>Medium</td>
</tr>
<tr>
<td>HMMI</td>
<td>1.0</td>
<td>0.43</td>
<td>Medium</td>
</tr>
</tbody>
</table>

**Figure 9** Cumulative error probability for multiple grid spacing

Fingerprints grid spacing of 0.5 m [1] or 1 m [32] or 2 m [33] is commonly chosen for indoor fingerprint based systems. In this paper we test our proposed model on different grid spacing from 0.5 m to 2 m, with a 0.5 m step size as shown in figure 9. The localization accuracy by using 0.5 m grid spacing for the proposed HMM achieves a localization error 0.12 m which is significantly smaller than Bayesian filtering used in [1] (0.77 m) as shown in Table 1. The complexity in table 1 means the effort on calibration process for creating radiomap or fingerprint database. The complexity is determined into 3 levels [27] as follows: relatively high complexity, medium complexity, simple complexity. The 0.5 m grid spacing requires 5920 (high complexity) calibration points, while 1.0 m grid requires 1480 (medium complexity). Comparing with other method, proposed hidden markov model interpolation (HMMI) shows high accuracy with medium complexity on 1.0 m (37*40) or 1480 fingerprint, the grid map are interpolated into 0.5 m spacing or 5920 fingerprint with a localization error (0.43 m) which is smaller than using HMM error (0.53 m) and maximum likelihood estimation (MLE) error (1.04 m) as shown in figure 10, 11.

**Figure 10** Localization accuracy vs. training grid density.

### Figure 11 Localization accuracy for 1 m grid spacing.

#### 5.2 HMM Tracking on Real Measurements

We used a 2D received signal strength data set investigated in [14] on the fifth floor of a five storey building of the Faculty of Computer Science and Information Technology, Riga Technical university. The area of the test-bed is approximately 860m², and includes eight classrooms, four offices, and the main hallway (as in figure 12(a) which displays the layout of the floor where the experiment was performed. A total of 82 calibration points are defined and 68 points test set was created for testing. The placement of the testing points mimics a person walking in a route through five classrooms, one office, and the hallway. The route is started at one point and finally ended at the very same point, visiting 34 different locations where each location is visited two times, each time facing a different direction. The measurement process, apart from that it is performed for only two orientations, is the same as for the calibration points (as in figure 12(b).

### Table 2: Simulation and experimental localization error results

<table>
<thead>
<tr>
<th>Access Points</th>
<th>WKNN Mean</th>
<th>WKNN Median</th>
<th>HMMI Mean</th>
<th>HMMI Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.4 GHz APs (5)</td>
<td>2.56</td>
<td>2.35</td>
<td>2.00</td>
<td>1.63</td>
</tr>
<tr>
<td>2.4 GHz APs (14)</td>
<td>2.33</td>
<td>2.16</td>
<td>1.64</td>
<td>1.37</td>
</tr>
<tr>
<td>2.4/5 GHz APs (14)</td>
<td>2.10</td>
<td>1.67</td>
<td>1.52</td>
<td>1.36</td>
</tr>
<tr>
<td>Outside APs (43)</td>
<td>7.14</td>
<td>6.51</td>
<td>5.35</td>
<td>4.65</td>
</tr>
<tr>
<td>2.4 GHz APs (57)</td>
<td>2.44</td>
<td>2.32</td>
<td>1.81</td>
<td>1.35</td>
</tr>
</tbody>
</table>
On average, the distance from one calibration point to the nearest other point is 3.7 m within the same room and 2.6 m when also the points from other rooms are considered. The number of APs that could be sensed from a location ranges from 2 to 13 with average of 7. We reconstruct our proposed HMMI to compare with the localization algorithm (WKNN) that use that test bed as mentioned in [14]. Table II shows the localization error comparison for both localization algorithms by using the 2.4 and 5.0 GHz access points.

6. CONCLUSION
In this paper, the problem of localization and tracking in indoor environment has been approached. The proposed tracking system architecture considers a static access point network and a moving client moving in it. In this spirit, a software simulator RPS ray-tracing and a real measurements RSS map of a monitored environment is used from experimental measurements. The formalization of the problem and the mathematical modeling have been developed and discussed in detail within the estimation theory framework. A novel approach based on HMM has been proposed to track location of moving terminals. We examined the performance of the proposed HMMI tracking algorithm with Bayesian filtering in [1] and MLE using RPS and also with WKNN with an experimental measurement. The proposed HMMI achieves a less complexity on reducing calculation effort with higher localization accuracy.

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