Efficient WiFi-Based Indoor Localization Using Particle Swarm Optimization

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Abstract. Location based services are rapidly gaining popularity in various mobile applications. Such services rely particularly on the capability to accurately determine the location of the user. Several techniques are already available to provide localization for static or mobile applications, GPS being the most popular. However, due to some limitations of GPS such as low accuracy, unavailability in indoor environments and lower signal quality in urban areas with high rise buildings, complementary solutions are essential to offer satisfactory service at all places all the time. This paper demonstrates the use of a widely available WiFi networking infrastructure for accurate and low-cost indoor localization. Most existing WiFi-based localization approaches employ radio signal strength indicator (RSSI) fingerprinting technique, which requires a great deal of pre-deployment effort. Our swarm-inspired optimization algorithm applies a simpler and efficient technique based on the radio propagation model of the wireless signal. The proposed technique is evaluated in simulation and is demonstrated to achieve excellent average localization error of about 4 meters in an area of 50 x 50 square meters, under noisy RSSI measurements.

Keywords: indoor localization, RSSI modeling, RSSI fingerprinting, particle swarm optimization.

1 Introduction

The recent advances in mobile Internet technology and the proliferation of a wide range of services are further accelerating the research and development effort for improved as well as new applications. Modern location based services (LBS) have evolved as a result of the technology integration of mobile Internet, smart phones, and Geospatial information. Knowledge of the user's location as well as locations of interest points in a given area are at the core of LBS and related services.

The problem of localization has been a core focus of research by many researchers in various fields, including mobile robotics, wireless sensor networks, mobile communication and internet technology. In general, different techniques may be utilized for outdoor and indoor localization. The focus of our study in this paper is indoor localization. Simplicity, cost, and accuracy of localization are common criteria for comparing different localization strategies. Ideally, it is desirable to have a

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technique that could be easily deployable without requiring initial setup, training or environmental adaptation. It is also necessary that the technique provides sufficient accuracy for the class of applications it is intended for. Obviously, a low cost solution is desirable to make the technology affordable for widespread applications.

Several techniques such as LANDMARC [1], Cricket [2], and Active Badge [3] are already available for indoor localization. However, these techniques deploy and rely on specialized infrastructure based on RFID, sonar, IR, or radio signals for the purpose of the localization thus adding to the deployment cost. Although the initial setup adds up to the cost of localization, these techniques often provide excellent accuracies. For example, Cricket - a triangulation based positioning technique using active ultrasound beacons, achieves an overall localization accuracy within 10 cm of the actual position. Such high levels of accuracies could be attractive for applications such as mobile robot navigation and object manipulation tasks.

On the other hand, several indoor and outdoor applications may not necessarily require such high levels of sub-meter accuracies. For example, when a person is navigating in an unknown indoor office environment or outdoors it might be sufficient to be able to localize within a few meters to aid find nearest interest points. For such applications where the accuracy requirement is relatively relaxed simpler and lower-cost localization techniques will be more attractive.

Two related radio frequency (RF) based localization techniques attract great interest mostly due to the fact that existing wireless communication infrastructure is exploited without incurring additional deployment cost. These methods rely on RF signals either from cellular towers or WiFi access points (APs). The localization solution based on reference information from cellular towers can be utilized anywhere cellular signals from at least 3 towers are available. For example, as part of the Federal Communications Commission (FCC) E911 rules wireless carriers in the US are required by law to provide a 911 caller's location to within 50 to 300 meters depending on the technology used [4]. Despite the limited accuracy of this technique it applies both indoors and outdoors providing global localization in extended geographical areas.

Our proposed solution is based on RF signals from WiFi access points. It assumes knowledge of the locations and transmit-powers of at least three access points. To minimize the effect of RSSI measurement uncertainties in the localization accuracy we employ a particle swarm based optimization algorithm that is found to result in robust performance in noisy environments. The main contribution of this paper is that we demonstrate an efficient and sufficiently accurate localization scheme for indoor localization using existing infrastructure with little initial setup or training.

The rest of this paper is organized as follows. Section II presents related work on RF based localization. Section III presents the wireless signal propagation model that is used in our localization solution. Section IV gives a short introduction to the PSO algorithm and describes the mapping of the localization problem to the PSO model. Section V presents the experiment and results. And finally the paper provides discussion and concluding remarks in sections VI and VII.

2 Related Work

In general, the localization techniques that use RF signals on existing networks employ a radio signal fingerprinting approach, model based techniques, or a combination with other localization methods [5]. In the radio signal fingerprinting method the RSSI measurements from all the radio transmitters in the region is mapped at each location of the environment. To localize a given device its RSSI readings are matched against the values stored in the map. RADAR [6] is an example of this technique which uses extensive offline data collection before real-time localization starts. There have been several improvements on this approach through the years as well as commercialization of the technology [7].

In a similar approach to RF signal fingerprinting but at a global scale a company called Skyhook [8] developed a WiFi positioning system (WPS). It collects and maintains a massive worldwide database of WiFi access points in major populated areas. Using the data and applying intelligent search techniques the company provides subscribers real-time access to location information. The company claims an accuracy of 10 to 20 meters by its core engine.

Alternative to the signal-fingerprinting and map-based approaches is a model-based technique that relies on the radio propagation property of the WiFi signal. In this case, the RF propagation model is used to predict the RSSI at various points in an environment. This method eliminates the cost of initial deployment, maintenance and the issue of scalability associated with the signal fingerprinting technique. But its localization accuracy may be slightly lower [9]. Previously proposed solutions using this approach include Chintalapudi et al. [5], Lim et al. [10], Madigan et al. [11]. Most of these techniques except [5] assume knowledge of the locations and transmit power of the APs, and/or rely on WiFi sniffers at known locations to provide anchor points for the localization algorithms. Chintalapudi et al. on the other hand assume access to GPS data at some locations in the environment. The GPS data provides known location fixes for the environment modeling created by a server. The system is configured in client-server model so mobile nodes query the server for their location information by sending requests wirelessly.

Like many of the existing techniques, our proposed method assumes knowledge of the locations and transmit characteristics of at least three access points in the operating environment. We modeled the localization problem as an optimization problem with the goal of minimizing the computed location error. Then an intelligent nature inspired problem solving strategy is applied to the optimal solutions for the localization problem. In this paper we employed the Particle Swarm Optimization (PSO) algorithm. The main reason for choosing PSO over other competing optimization techniques is due to its simplicity and proven performance to deal with noisy optimization problems. For example, on a similar problem of emission source localization in noisy environments we demonstrated the superior performance of PSO over Differential evolution (DE) and Matlab's non-linear least squares (LSQ) optimization tool [12].

3 Wireless Signal Propagation Model

In our studies we assume an environment with IEEE 802.11 wireless communication at 2.4 GHz band. There are several experimental and theoretical studies of radio signal propagation in indoor environments [13]. In this paper the log-distance path loss (LDPL) model is used to predict RF signal attenuation as a function of distance between an AP and a WiFi receiver. This model is given by Equation (1) below:

$$p_d = P_0 - 10 \cdot \alpha \cdot \log(d) + R. \tag{1}$$

where pd is the received power in dBm at distance d (in meters) from the transmitter. P0 is the signal strength 1 meter from the transmitter, α is known as the path loss exponent, and R represents a random variable for capturing the variations in the RSSI readings due to multi-path effects, physical barriers in signal path and other imperfections in the model. The parameter α is dependent on the environment, i.e. type of construction material, architecture, location, temperature, humidity, etc. Empirical measurements of α in the literature report values in the range 1.8 to 5 depending on the level of obstruction [11]. Lower value of α correspond to lower signal path loss. For example, for free space propagation a value of 2.0 is used and for office environment with wall partitions, furniture and people a value of 2.5 would be a reasonable choice.

4 Particle Swarm Based Localization Algorithm

Particle Swarm Optimization (PSO) was inspired by the social swarming behavior of bird flocks, fish schools, and bee swarms. It was first developed in 1995 by Kennedy and Eberhart [14]. Individual particles in a particle swarm represent candidate solutions for the optimization problem. Initially, at the start of the optimization algorithm the PSO particles are assigned random initial positions in the search space. The particles are then moved around in the parameter space by using systematic rules to adjust their velocities and positions, in response to the swarm's experience in locating quality solutions.

The social interaction of the particles in the swarm shapes the dynamics the optimization algorithm. Thus, the performance of the individual particles in the swarm is influenced by a combination of their personal and social best experiences. In effect, the particles tend to be attracted to the best solution they have individually found and the best solution that any particle in their neighborhood has found.

Different PSO models have been proposed over the years to target different classes of problems. Two of the most widely known models are the constriction-factor and inertia-weight forms of the PSO algorithm, both of which have been demonstrated to be effective for general optimization tasks. The governing equations for the constriction-factor form of the PSO algorithm are given by Equations (2) and (3):

$$v_{ij}(t+1) = \chi \cdot \left(v_{ij}(t) + \varphi_1 \cdot r_1 \cdot (p_{ij} - x_{ij}(t)) + \varphi_2 \cdot r_2 \cdot (p_{gj} - x_{ij}(t))\right). \tag{2}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1). \tag{3}$$

The quantity χ is called constriction-factor. The quantity is the personal best position of particle and is the global best position in the entire swarm. and represent the learning rates that control the degree of influence of the cognitive and social components. and are independently generated random numbers in (0,1). They contribute to the stochastic behavior of the algorithm to allow random exploration of the search space in the surroundings of the personal and neighborhood best positions. The performance of each particle is measured using a problem specific pre-defined fitness function.

In our proposed solution strategy for the problem of localization we assume the presence of at least three reference APs with known locations and transmit powers. When we want to compute the (x, y) location of a point in space within the operating environment, we will first collect RSSI readings from the three APs. Then we apply the swarm inspired optimization method on the LDPL model to reach at an optimal localization with minimum estimation error. The fitness function for the optimization problem is derived with the goal of minimizing the sum of the squares of the errors between the actual RSSI readings from all the APs at the unknown location (x, y) and the theoretical values that would be obtained from the LDPL model, computed over all the reference APs.

$$f = \sum_{\forall APs} \left(p_i - P_{0i} + 10 \cdot \alpha \cdot \log(d_i) \right)^2 . \tag{4}$$

where, pi is the RSSI reading at the unknown location from the ith access point. P0i is the RSSI reading at 1 meter radius from the ith AP. di is the distance in meters of the unknown node location from the ith AP. In equation (4) di is the unknown quantity that will be solved as part of finding the solution for the unknown location (x, y).

The PSO algorithm initially starts by assigning the particles in the swarm random positions in the search space. By evaluating the fitness function for each particle the algorithm determines how close they are to the actual position. Particles that are located far away from the desired location (x, y), whose position is being computed, result in larger values of f corresponding to higher estimation errors than particles closer to the actual node location. Then, in successive iterations the algorithm tries to update the particles' velocities and positions using the PSO equations so as to improve their fitness values.

5 Experiment and Results

For our simulation experiment we considered the following environmental layout, shown in Fig. 1. Three different dimensions of the same environmental layout were considered to study the effect of the size of the working areas on the estimation accuracy. Experiments were conducted on the following three sizes of the environment:

a) 25 x 25 square meters
b) 50 x 50 square meters
c) 100 x 100 square meters

In each case three APs were placed far apart from each other in a triangular formation. Then randomly generated points were distributed all over the environment. The PSO based localization algorithm computes the locations of these points based on their RSSI measurements.

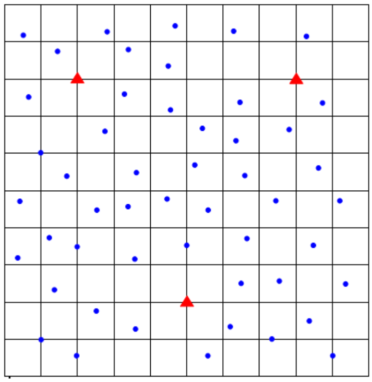

Fig. 1. Layout of the test environment with randomly placed test points (the triangles are APs, the dots are points whose localization is to be computed)

The only information the optimization algorithm has at the its start is the set of RSSI measurements at the unknown position from the three WiFi access points. The locations and transmit powers of the access points is assumed known, and also the path loss model of the radio signal in the operating environment.

To study the impact of the measurement uncertainties in the RSSI values due to environmental effects, zero mean Gaussian distributed random noise was introduced in the emulated readings of the radio signals. The standard deviation of the noise was varied from 0 to 5, to see how it impacts the localization accuracy.

To minimize the impact of noise the localization algorithm takes 30 samples of the RSSI readings at each unknown location and takes the average value. Using the RSSI readings and knowledge of information about the three reference access points the PSO algorithm computes the localization of each point. For the LDPL model in the problem formulation we used a value of $\alpha = 2.5$ which was assumed to work fine for a single floor office building with some partitioning walls and corridors.

The PSO parameters used in the simulation are swarm size of N = 50, constriction factor, $\chi = 0.729$, learning rates, = = 2.05.

The performance of the localization algorithm is evaluated by calculating the localization error which is computed as the Euclidean distance between the estimated location (x', y') of the point from the algorithm and its actual location (x, y).

Fig. 2, 3 and 4 present the way the localization algorithm performs over the three environmental dimensions.

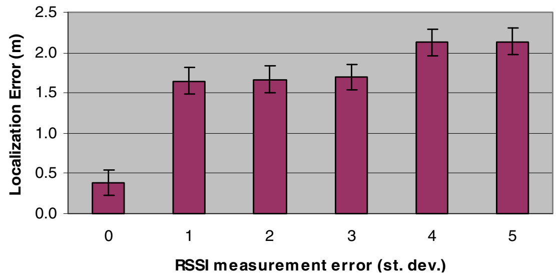

Fig. 2. Localization accuracy on 25 x 25 sq. meters. The horizontal axis shows st. dev. of the Gaussian noise in the RSSI measurement error.

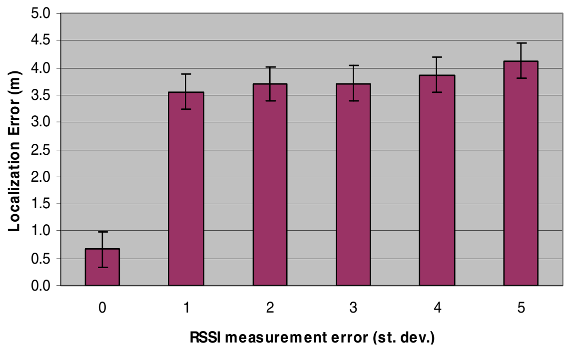

Fig. 3. Localization accuracy on 50 x 50 sq. meters. The horizontal axis shows st. dev. of the Gaussian noise in the RSSI measurement.

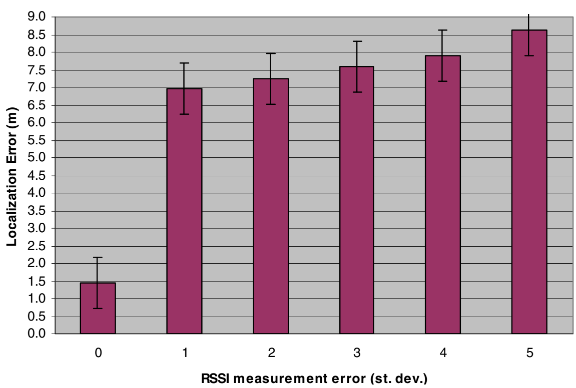

Fig. 4. Localization accuracy on 100 x 100 sq. meters. The horizontal axis shows st. dev. of the Gaussian noise in the RSSI measurement.

6 Discussion

From Fig. 2, we see that for the smallest size operating environment (25 x 25 sq. meters), the average maximum localization error is limited to about 2 meters for the maximum setting of the noise level. From Fig. 3, for the 50 x 50 sq. meters operating environment, the average maximum error is shown to be limited to about 4 meters for the maximum noise level. And from Fig. 4, for the 100 x 100 sq. meters operating environment, the average maximum error is shown to be about 8.5 meters at the maximum noise level. From these results we observe that the localization error follows more like a linear pattern as a function of the dimension of the operating environment.

To compare the performance of our algorithm to that of RSSI fingerprinting techniques, consider the problem dimension 50 x 50 square meters which is close to the size of the environment reported in RADAR [6]. The 50 percentile (median) error of our algorithm at the maximum level of Gaussian noise is about 3.4 meters. This result is only slightly worse than the best 2 to 3 meter achieved by RADAR which relies on cumbersome offline data collection.

A resolution of 3 to 5 meters for medium size environments could be quite good enough for common indoor applications. Our goal is to deploy such localization tools on autonomous mobile robots that could benefit from the WiFi based global localization for navigational tasks, while improvements on the accuracy can be achieved using additional sensors for local perception. For example, if vision or other sensors are available on board the mobile robot, information obtained from visual landmarks could be used to aid in improving the localization accuracy.

When examining the execution performance of our proposed algorithm, we find that compared to other model based methods the PSO-based solution is found to be efficient and converges fast in less than one second on a Dell Latitude E5400 laptop. In contrast, the result reported in [8] takes extra long off-line training times (16 to 65 minutes on a Lenovo T61p laptop) for building the RF model using Genetic Algorithm based technique.

7 Conclusion

The significance of our PSO based localization technique using existing WiFi infrastructure is that it requires little initial setup. It can be easily deployed for use by humans or mobile robots as long as WiFi access from at least three APs can be obtained. Unlike other techniques, such as [5] and [8], there is no offline training required. These are important properties especially in scenarios when there is no prior information about the environment or when there is no time to gather fingerprinting data that would be needed for some of the other methods.

The proposed technique is evaluated in simulation and is demonstrated to achieve average localization error of about 4 meters in an area of 50 x 50 square meters, under noisy RSSI measurements. This is reasonably sufficient accuracy for the class of target applications the technique is meant for. In future work we will implement and carry out experiments in real physical environments and evaluate its performance. Methods of automatically determining the parameters of the APs will also be examined.

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