Robust Indoor Positioning Based on Received Signal Strength

Kamran Sayrafian-Pour[1], Julio Perez[2]

[1]*Information Technology Laboratory, National Institute of Standards and Technology, USA*
ksayrafian@nist.gov

[2] *Department of Computer Science, Swiss Federal Institute of Technology Zurich, Switzerland*
julio.perez@alumni.ethz.ch

Abstract

A positioning algorithm based on the relative order of the received signal strengths is discussed. This algorithm in conjunction with the ray-tracing propagation model can have promising performance for indoor environments without any needs for extensive set of a priori training. Enhancements to the positioning algorithm will be proposed and investigated. Two sets of experimental results with 802.11-based infrastructure and MICA2 motes are presented to demonstrate the system capability and performance in practice.

Keywords: Indoor Positioning, Ray-Tracing, Radio-Map

1. Introduction

Positioning techniques based on the Received Signal Strength (RSS) ([1],[2],[4]) have been extensively studied in literature. These techniques, although sometimes less accurate compared to more complex range-based techniques, are very simple to implement and offer low cost and effective alternatives for most applications. The core idea is to establish a one-to-one relationship between the received signal strength from several reference nodes and the current position of the mobile. One such system that has been implemented on the existing wireless local area network infrastructure is RADAR [2]. The main drawback of the RSS-based techniques is the need for a measurement-based training phase, during which the radio map of the environment is created. This map essentially contains the received signal strength from the reference nodes throughout the building. The process to generate a radio map is not only labor-intensive and costly, but also very sensitive to changes in the environment and possible sources of interference in the building.

A simple alternative to generate the radio map for RSS-based positioning system is using an appropriate propagation model instead of the actual measurements. For example, deterministic channel models such as the ones based on ray-tracing are a good candidate for this problem. However, in these models, only simple high-level building information, such as layout is used and other detail information about the environment such as the exact radio properties of the walls and other obstacles affecting the RSS such as furniture are often ignored. The accuracy of the predicted signal strength can be highly dependent on this detail information which is almost impossible to capture in the model. Therefore, the performance of the positioning system will heavily depend on the details of the model.

We have implemented a prototype system based on the Euclidean distance of the RSS vectors (i.e. similar to RADAR) and experimentally tested its performance in the fourth floor of our building (i.e. NIST North). The system block diagram and the building layout are shown in figures 1 and 2 respectively.

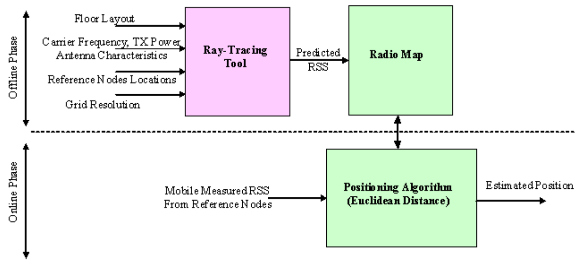

Figure 1. System block diagram to evaluate model-based radio map

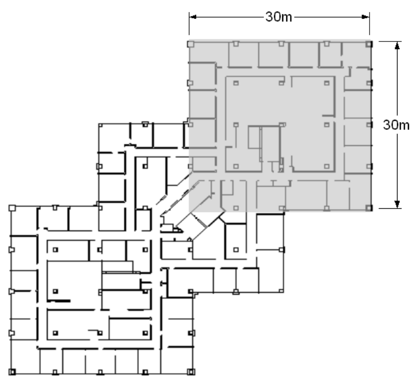

Figure 2. Test area in the NIST North building

Figure 3 illustrates the dependency of the positioning accuracy on different wall-types used in the ray tracing model. The observed variation (i.e. as much as 65%) in performance is mainly due to the fact that the algorithm is based on the numeric values of the received signal strengths; therefore any error in the predicted RSS values (i.e. caused by the ray-tracing model) will directly reflect on the accuracy of the positioning system. This means that the system performance could potentially be improved if there are positioning algorithms that do not rely on the exact values of the predicted RSS.

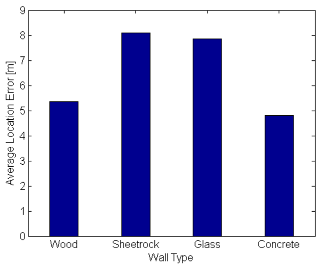

Figure 3. Average location error for various wall types

Authors in [3] have suggested using the relative ordering of the RSS from all reference nodes as a signature to identify the position of a mobile. Their algorithm referred to as "Ecolocation", generates the pair-wise ordered sequence of the reference nodes by ranking them on the collected signal strength measurements. Assume that R_i is the RSS from the reference node 'i' at the mobile's location (x,y). Then, given α reference nodes, their proposed algorithm in the online phase generates the following constraint matrix for every position of the mobile.

$$M_\alpha(x,y)=[c_{ij}(x,y)] \qquad i,j=1,2,....,\alpha$$

where

$$c_{ij}(x,y)=\begin{cases}+1 & R_i(x,y)>R_j(x,y)\\ -1 & R_i(x,y)<R_j(x,y)\\ 0 & R_i(x,y)=R_j(x,y)\end{cases} \qquad \forall i\neq j$$

and $c_{ij}(x,y)=0 \quad \forall i=j$

In the offline phase, the radio map is constructed by generating the constraint matrices for a grid of points overlaying the layout. Each entry in the radio map is a constraint matrix resulting from the pair-wise ordered sequence of reference nodes based on their "distance" to the given grid point (x_k,y_k) as follows:

$$M_\alpha(x_k,y_k)=[c_{ij}(x_k,y_k)] \qquad i,j=1,2,....,\alpha$$

where

$$c_{ij}(x_k,y_k)=\begin{cases}+1 & d_i(x_k,y_k)<d_j(x_k,y_k)\\ -1 & d_i(x_k,y_k)>d_j(x_k,y_k)\\ 0 & d_i(x_k,y_k)=d_j(x_k,y_k)\end{cases} \forall i\neq j$$

and $c_{ij}(x_k,y_k)=0 \quad \forall i=j$

It is claimed that although ranking based on distance does not always match with RSS-based ranking, the inherent redundancy that exists in each constraint matrix (i.e. inherent insensitivity to the absolute RSS values) gives rise to an acceptable performance for the positioning algorithm. The mobile position is estimated by finding the location on the radio map that has the closest constraint matrix to the one experienced by the mobile. The closeness metric here is similar to Hamming distance.

In order to enhance the performance of this algorithm for indoor environments, where distance-based ranking mostly does not match RSS-based ranking, we first propose to use a ray-tracing tool to generate the set of all constraint matrices required to build the radio map. Our conjecture is that for this particular positioning algorithm even a crude layout model, that can be used for the ray-tracing, will produce a more accurate radio map than one generated by simple distance-based approach. As mentioned before, although the penetration and/or reflection loss of each wall cannot be modeled accurately in a ray-tracing tool, the overall RSS ranking will be more accurate compared to the methodology used in [3]. The only additional input needed is a crude map of the building layout. The information regarding the dielectric parameters of each wall is not required. In fact, the exact value of these parameters, as will be shown later, will not have a big impact on the entries of the radio map; thus rendering the approach robust.

Also, an important assumption in [3] is that all reference nodes can be heard by the mobile node at all locations throughout the environment. In other words, full coverage of the entire service area by each individual reference node is required. This assumption could be unrealistic in scenarios where the size of the area is large or reference nodes have limited power (e.g. sensor networks). Consequently, this implies that the algorithm is not scalable in terms of the size of the indoor environment. Here, we propose to modify the constraint matrix definition to include cases where reference nodes have limited coverage area which is smaller than the size of the building where positioning service needs to be offered. This modification enables the system to be easily scaled.

We will discuss our proposed modifications and the resulting performance improvement in section 2. System implementation with MICA2 motes and an 802.11-based prototype are presented in section 3. Existence of an optimal power allocation for reference nodes is explained in section 4 and finally reference node deployment strategy is briefly studied in section 5.

2. System Modeling and Performance Evaluation

We propose a new set of constraints that takes into account the coverage area of each reference node by considering the mobile node's receiver sensitivity. When it comes to the positioning problem, it is important to note that knowledge of being outside the coverage area of a particular reference node could be as informative as knowing the RSS value associated with that node. In a large area, not all reference nodes can be heard by the mobile at all times; therefore, we can extend the entries in the constraint matrix to include scenarios where the mobile is outside the coverage area of one or some of the reference nodes. This would happen if the RSS from a given reference node falls below the mobile node's receiver sensitivity. Receiver sensitivity is the minimal signal power that is required for a receiver to be able to detect the received signal. In other words, for a fixed reference node's transmission power, receiver sensitivity determines the extent of the coverage area for that reference node. If R_{sens} denotes the receiver sensitivity, then the following new entries for the constraint matrix can be defined in order to better capture information regarding the mobile's position.

$$M_{\alpha}^{*}(x,y)=[c_{ij}(x,y)] \qquad i,j=1,2,....,\alpha$$

where $\forall i \neq j$

$$c_{ij}^{*}(x,y)=\begin{cases} +1 & R_i(x,y)>R_j(x,y) \\ -1 & R_i(x,y)<R_j(x,y) \\ 0 & R_i(x,y)=R_j(x,y) \\ +2 & R_j(x,y)<R_{sens}<R_i(x,y) \\ -2 & R_i(x,y)<R_{sens}<R_j(x,y) \\ +3 & R_i(x,y)<R_{sens} \,\&\, R_j(x,y)<R_{sens} \end{cases}$$

and $\quad c_{ij}^{*}(x,y)=0 \quad \forall i=j$

This extended set of constraints not only makes the system scalable in terms of the coverage area but also enhances the positioning accuracy. To evaluate the effectiveness of the proposed modification along with using a deterministic channel model to generate the radio map, we have implemented the algorithm and used a ray-tracing tool as a mean to generate all constraint matrices needed for the positioning algorithm. This is schematically shown in figure 4.

In this study, we have used Wireless System Engineering (WiSE) as our ray-tracing tool to predict the average received signal strengths from each reference node [5]. We refer to the positioning algorithm with the ray-tracing-based radio map and the extended set of constraints as Comparative RSS (CRSS). We have simulated the performance of the positioning algorithm in [3] and compared it with CRSS. The block diagram in figure 5 describes the simulation platform.

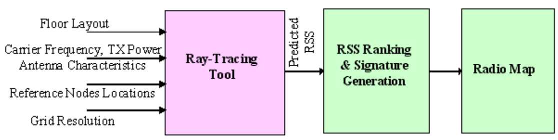

Figure 4. Radio map generation based on the ray tracing and RSS ranking

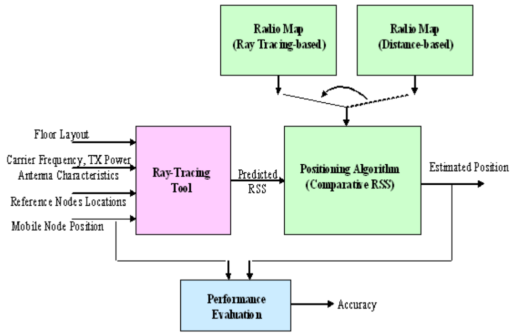

Figure 5. System block diagram for performance evaluation

Figure 6 shows the gain that is achieved in lowering the average error in the estimated position by the CRSS system. The graph displays average error in the estimated position for various number of reference nodes that have been placed in pre-determined locations in the 4th floor of the NIST North building (Figure 2).

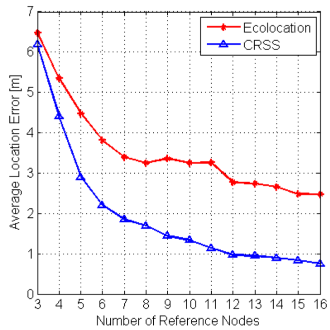

Figure 6. CRSS vs. Ecolocation (2.4 GHz, 900 m^2 test area)

The above results were obtained by considering 400 random test locations for the mobile and calculating the average error for the given number of reference nodes. The RSS of each of the 400 mobile test positions were generated using the ray tracing module which in reality might not match their corresponding measured values. So, in order to capture the effect of error in the predicted RSS on the system performance, an error component needs to be added to each predicted RSS prior to the evaluation process (see Figure 7). This error component which can be modeled as a Lognormal random variable represents how accurate the ray-tracing module can predict received signal values throughout the environment. Details of the modeling procedure have been omitted for brevity.

In section 1, we showed that this error has a great impact on positioning algorithms such as RADAR that solely rely on the numeric values of these predictions. It is interesting to see how the CRSS algorithm performs for large error intensities.

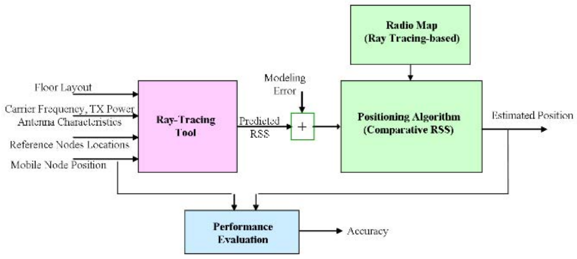

Figure 7. System block diagram with modeling error

Figure 8 shows the system performance for various error intensities (i.e. μ=0 and σ=0,2,4,6). The error component (in dB) is an i.i.d. lognormally distributed random process with mean μ and variance σ^2. As observed, CRSS exhibits a graceful degradation of performance as error intensity increases. Also, CRSS is completely resilient to dc errors (i.e. μ). This again is due to the fact that the absolute value of the RSS is not used by the algorithm; and therefore, any bias in the predicted RSS values will not affect the system's performance.

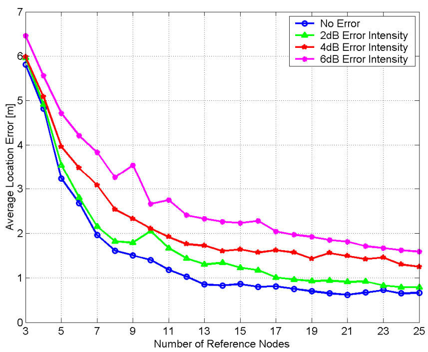

Figure 8. Degradation of the performance with modeling error

3. System Implementation

We implemented the CRSS algorithm with an 802.11-based system. The reference nodes were Intrinsyc's CerfCube embedded systems equipped with compact flash 802.11 wireless LAN cards with RF output power of 14 dBm. 14 reference nodes were located throughout the 4th floor of the NIST North office building as shown in figure 9. In this experiment, the transmit power of each cube is high enough so that it covers the entire area under test. Therefore, the mobile can hear all reference nodes regardless of its position.

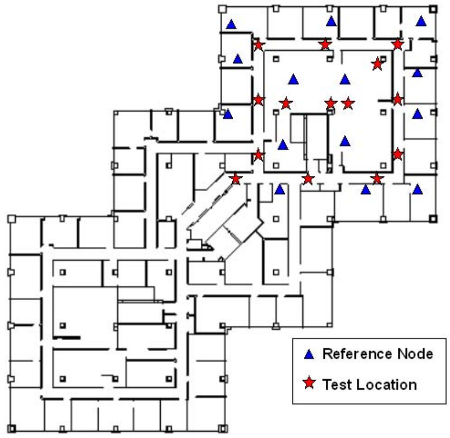

Figure 9. Node deployment and test locations

As shown in figure 9, 14 different mobile test locations were also chosen. The true versus estimated mobile positions for this experiment has been plotted in figure 10. The average and standard deviation of the position estimation error are 2.02m and 1.64m respectively. The system generally exhibited great performance. The top middle and right hand side correspond to the lab location where lots of metal shelves are located. This is why the error at those locations is more than everywhere else.

Our experiment shows that with a node density of 0.015 nodes/m^2 (i.e. 14 reference nodes in 900m^2 area), an average error of about 2 meters is achievable. It has been shown that this is almost the best achievable average error for systems that require extensive offline measurements [4]. Therefore, this methodology could be extremely promising for practical deployment of indoor positioning systems.

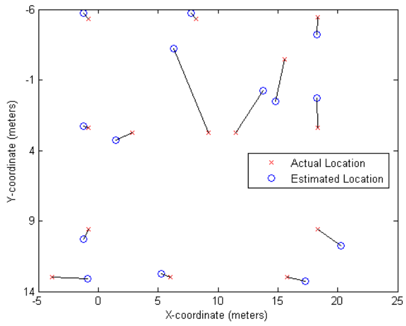

Figure 10. Position estimation error

Figure 11 illustrates the dependency of the positioning accuracy when various wall types are used in the ray tracing model. As observed, the CRSS system is far less sensitive to the variation in the material types (i.e. radio properties) of the walls in the model. Therefore, it is an appropriate candidate for an RSS-based system that can have acceptable performance without any training phase.

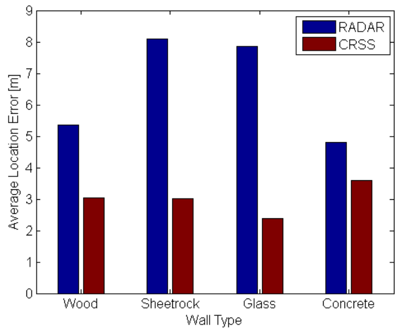

Figure 11. Average location error for various wall types

The performance of our proposed positioning system was further studied by conducting experiments with the 900 MHz TinyOS Crossbow MICA2 Motes deployed in the NIST North, 4th floor building. 9 reference nodes were deployed in the test area as shown in figure 12. Also, in order to see the effect of the CRSS system, various power levels ranging from -20dBm up to 5dBm were used.

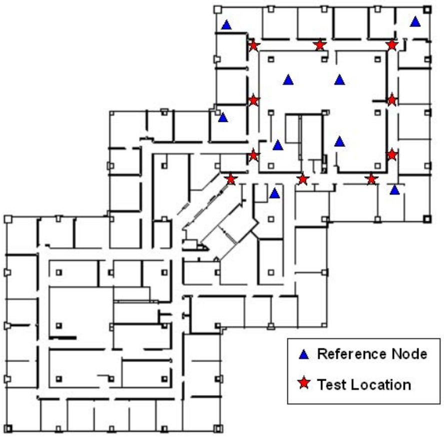

Figure 12. Berkeley motes node deployment and test locations

In order to take advantage of the extended set of constraints in the CRSS system, the receiver sensitivity of these MICA2 motes needs to be determined first. To obtain this threshold, we conducted a separate experiment which measured the average RSS versus packet loss for a total of 120 randomly chosen transmitter-receiver locations in the NIST north building. To measure the RSS between each transmitter-receiver pair, 200 packets were sent by the transmitter. The receiver then computes the average RSS over all received packets. This was repeated for different transmission power levels. The result of this experiment shows that we can take -95 dBm as the practical receiver sensitivity for the CRSS system. Details of this experiment are omitted for brevity.

With the knowledge of the coverage limit of each reference node, we conducted experiments for various mobile test locations as shown in figure 13. The true versus estimated locations for this experiment has been plotted in figure 13. The average and standard deviation of the position estimation error for the CRSS system with only 5dBm reference node's transmission power were 2.46m and 1.53m respectively. In comparison, the experiment with the CerfCubes resulted in 3.25m of average error for 9 reference nodes each with 14dBm transmission power. This proves the gains (both in accuracy and power consumption) that can be achieved by the extended set of constraints in the CRSS system.

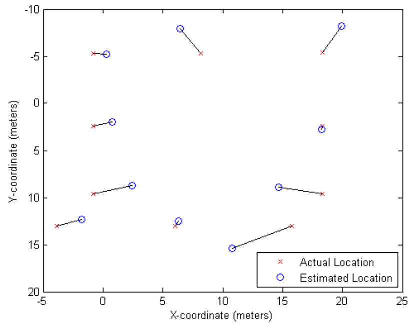

Figure 13. Position estimation error with the mote experiment

4. Optimal Power Allocation

An important underlying assumption in all of the results so far, is equal transmission power for all reference nodes at all times. This transmission power basically controls the coverage area provided by each reference node. The shapes of all these coverage areas greatly impact the accuracy of the positioning algorithms discussed in this paper. For a given building layout and the receiver sensitivity, the coverage area directly depends on the node's location inside the building and its transmission power. In this section, we would like to show that there exists a non-uniform power allocation for reference nodes that could result in better performance in terms of the positioning accuracy. For a general layout and more number of reference nodes, the problem of finding this optimal assignment turns into a highly non-linear optimization problem. Simulated Annealing is a powerful method that has been shown [6] to be able to achieve global optimum without getting trapped at local minima. Here, we also propose to use Simulated Annealing to identify node's transmission power for 4 reference nodes deployed in the NIST North building.

Table 1 shows the results of simulated annealing for the given node deployment. Under non-uniform power allocation for 4 reference nodes, an average error of 3.25m can be achieved. This is 20cm better than the uniform power allocation case. It should be noted that proper reference node placement throughout the environment can also affect the system performance. However, the joint problem of optimal node deployment and power allocation is an extremely difficult problem. We will briefly discuss the node deployment further in section 5.

Table 1. Simulated Annealing results

	Uniform Power Allocation [mW]	Non-Uniform Power Allocation [mW]
Reference Node 1	0.05	0.05
Reference Node 2	0.05	0.11
Reference Node 3	0.05	0.03
Reference Node 4	0.05	0.3

5. Reference Node Deployment

Position of the reference nodes is another set of parameters that can impact the overall system performance. In open spaces (e.g. clutter-free), it is logical to expect that a symmetric placement of reference nodes would be the best strategy to follow; however, in general, at indoor environment, this could become a challenging problem. The complexity arises from the fact that usually in positioning systems mobile's visibility by several reference nodes (or vice versa) is required and the building layout could have a great impact on this issue. It would be an extremely desirable feature if the robustness provided in the positioning methodology can absorb such impacts and reduce the sensitivity of the overall performance to the exact location of the reference nodes.

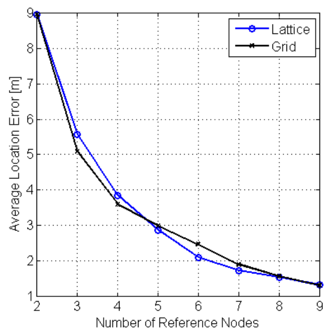

Figure 14. Adaptive versus fixed reference node deployment

In the results provided so far, we have considered an overlay lattice and used the full (or partial) points on this lattice as reference node location. In other words, adding a reference node is done independently of the system performance for the current number of nodes. Adaptive node placement strategies have been proposed to increase the quality of spatial localization. The authors in [7] have suggested several algorithms that take advantage of the system performance for a given number of nodes before deciding on the location of the next reference node. We have implemented one such algorithm called "Grid" and verified its performance against our fixed lattice approach. As observed in figure 14, adaptive node deployment displays similar performance to the fixed lattice approach. This means that the positioning algorithm also provides robustness against possible imperfections in the exact placement of the reference nodes.

6. Conclusion

The indoor positioning problem discussed here basically forms a multi-dimensional joint optimization problem. Among the parameters affecting the system performance, we have considered the number of the reference nodes, their locations, transmission power, the building layout and its radio properties. We have studied the effect of each one of these parameters individually and pointed out various strategies to improve the achieved accuracy. The focus in this research was to provide robust methodologies that are implementable on RSS-based, low cost, low complexity infrastructure. An essential step in doing so is to eliminate the offline training phase that could be an obstacle in practical implementation of these systems. By integrating any simple ray-tracing program with the proposed positioning algorithm, a complete system can be designed that is quickly deployable on 802.11-based systems or sensor networks. Further studies need to be done before such systems can have widespread applications in our daily life.

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