Evaluation of RSS-based Position Tracking using WSNs for Resource Localization in an Indoor Construction Environment

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Abstract: Timely information of construction resource is always a concern and an essential task for construction engineers and managers. In the recent past, Wireless Sensor Networks (WSNs) have emerged as a promising means to improve the current construction localization applications due to the ease of deployment and expandability to large scale construction projects, low cost, and capacity to function efficiently under dynamic and rough environments. Received Signal Strength Indicator (RSSI) based localization is a popular technique especially for indoor environments, where satellite based positioning is infeasible. This study evaluates multilateration localization, a popular localization technique, in construction environments as well as a second, profiling-based, localization technique. Both techniques RSSI values collected in a WSN. Indoor experiments were conducted and their results reveal that acceptable position accuracy can be obtained with the profiling-based architecture.

1 INTRODUCTION

The construction industry is currently seeking to employ techniques that can reduce project completion time and cost, and improve project productivity and performance. Awareness of resource status, such as the location of tools, equipment, materials and workers, can play an important role in attaining cost and timeliness objectives.

Localization is a building block for implementing higher level functionalities based on positioning technologies, such as tracking, monitoring, and data collection. Previous research on the use of wireless technologies for localization in construction sites, has focused mainly on localization in open areas, for instance, tool tracking and locating materials in a storage yard (Song et al., 2006); (Goodrum et al., 2006); (Ergen et al., 2007); (Teizer et al., 2007); (Chin and Yoon, 2008). However, provision of a reliable localization technique for indoor or partially covered environments (where satellite-based positioning such as GPS is infeasible due to signal obstruction) is a challenge. Wireless sensor network (WSN) technologies provide flexible data acquisition and improved communication automation suitable for construction environments. This is due to their ease of deployment and expandability to large scale construction projects (Skibniewski and Jang, 2009). It is therefore natural to co-opt WSNs for localization purposes as well. The cost-effectiveness and capacity to work efficiently under dynamic and harsh environment are the other factors that make WSNs an appropriate technology to improve current tracking and monitoring practices in construction (Shen et al., 2008).

The objective of this paper is to study a low cost and accurate indoor localization and resource tracking methodology utilizing WSNs for construction projects. First, we investigate the feasibility and application of a geometric multilateration localization algorithm on the basis of received signal strength (RSS) measurement based on a ranging technique. To overcome the limitations of multilateration, we use an alternative technique, that determines the location of mobile sensor nodes ("tags") by profiling the RSS collected by stationary sensor nodes ("pegs") with known locations. An experiment was conducted in a parking lot in order to evaluate the potential and confirm the capability of RSS-based localization in construction sites.

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2 LOCALIZATION TECHNIQUES

The first, and well-known technique, we consider is a range-based multilateration technique. Given that the ranges between a mobile node and three or more stationary nodes are determined, the location of the mobile node can be calculated by applying the geometric multilateration algorithm. RSSI-based ranging is low-cost and simple to implement and does not require expensive, specialized, infrastructure (Haque et al., 2009).

The RSS-based range measurement is developed based on propagation-loss characteristics of radio frequency signals. One of the factors influencing RSS values obtained by a wireless device is the distance between transmitter and receiver, as this distance causes attenuation, "path loss," captured in the RSS values. One usually applies a "standard" propagation model, such as the ITU indoor signal propagation model which is considered applicable to complicated, hostile, indoor environments delimited by walls. It is given by (Stallings 2005, Shen et al. 2011):

$$L_{dBm} = 10log_{10}(f) + Nlog_{10}(d) + Lf(n) - 147.56 \tag{1}$$

where N is the distance power loss coefficient and $Lf(n)$ denotes the floor penetration loss factor which can be omitted for line-of-sight transmission. It is noteworthy to mention that N is not a specific value for construction environments, and can only be determined based on collecting field data for the specific environment (Shen et al., 2011). Then, the received signal strength at distance d can be calculated by essentially solving equation (1) for d. Using the estimated distances from the known coordinates of the reference nodes, the location is calculated based on multilateration.

2.1 LEMON

An alternative to range-based localization is range-free localization. An example of a range-free localization is LEMON (Haque et al., 2009). It consists of two phases: 1) profiling and 2) actual localization. In the first phase, a database of RSSI readings is populated for transmissions received from tags at known locations. The database consists of samples which are stored as triplets $< C; \Omega; \tau >$ in which C represents the known coordinates of the sampled point, Ω stands for the association set (which comprises receiver ID and the RSS value received by that Receiver), and τ symbolizes the class of sample (e.g., channel/frequency used, and any other pertinent transmitter configuration information). The second phase, i.e., the actual localization of tracked tag at an unknown location, is similar to the profiling stage with the only difference being that C is unknown.

In the localization stage, the server compares the tracked tag's RSS, as reported measured by all the receivers in the monitored area, against the RSS of each profiled reference point and evaluates the difference between the tag and all the profiling points. If $\Omega = \{w_1, \dots, w_K\}$ and $\Psi = \{\psi_1, \dots, \psi_K\}$ are assumed to be two association's sets, the distance between these sets will be:

$$D(\Omega, \Psi) = \sqrt{\sum_{j=1}^{N} (R_\Omega(j) - R_\Psi(j))^2} \tag{2}$$

where N is the total number of receivers in the network and $\mathrm{R}_\Omega(\mathrm{j})$ is defined as $\mathrm{r_j}$, if the pair $< \mathrm{p_j}, \mathrm{r_j} >$ occurs is found in Ω, and 0 otherwise. Therefore, the server evaluates the signal-space distance of each pre-selected sample (its association set) from the tag's association set, representing the combined momentary perception of the tag's RSS by all the receivers (pegs) that can hear it.

It should be emphasized that, contrary to range-based techniques, no attempt is made to relate the distance in the signal space to a Euclidean distance from the peg. The next step is the selection of an arbitrary number, K, of profiled samples with the smallest distance from the tracked tag. This is called the "best matched" set of profiled points. Subsequently, the coordinates of the selected samples are averaged to produce the estimated coordinates of the tag. The averaging formula biases the samples in such a way that the ones with a smaller distance contribute with a proportionally larger weight. The biasing reflects the intuition that a smaller signal-space distance implies very likely a more reliable signal, by virtue of being closer to the corresponding receiving peg. If D_{max} is the maximum distance among the best K selected samples and $S_d = \sum_{i=1}^{K} D_i$ is the sum of all those distances then the tag coordinates are estimated as:

$$x_{est} = \frac{\sum_{i=1}^{k} x_i (D_{max} - D_i)}{K \times D_{max} - S_d} \tag{3}$$

$$y_{est} = \frac{\sum_{i=1}^{k} y_i (D_{max} - D_i)}{K \times D_{max} - S_d} \tag{4}$$

where (x_i, y_i) are the coordinates associated with sample i.

3 EXPERIMENTS

The infrastructure nodes that we used for assessing the proposed localization architecture are low-cost, low-power wireless devices. The nodes utilized for our experiments make use of the CC1100 RF module from Texas Instruments operating within the 915MHz band. From an operational point of view, the node is called a "peg" when it captures signal strength. The pegs' locations are fixed (static nodes) and their precise location needs to be known. A monitored device, which is a node of the same type as a peg, is called a tag whose location needs to be determined. The experiments were conducted by deploying a number of nodes in an underground parking lot over an approximately 12m×9m rectangular layout. The environment incorporated certain features one can find in a construction environment, such as steel access doors, metallic cages, concrete columns, and power cables, and was subjected to occasional (uncontrolled) pedestrian and vehicular traffic. Fixed nodes were distributed at the corners of the 12m×9m rectangular area and a node (to be localized) was moving along a rectangular path of 8m×6m within that area. The peg placement (red squares), tracked tag (blue circles), and profiling points for LEMON (× marks) is depicted in Figure 1.

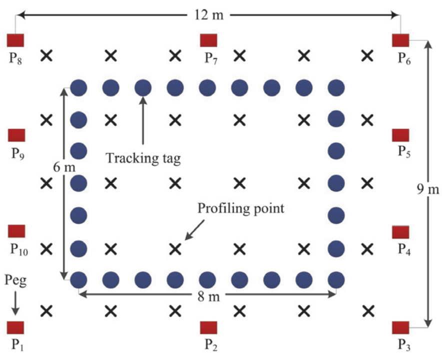

Figure 1: Experimental layout.

A simple visual comparison of the multilateration (Figure 2) and LEMON (Figure 3) results points to a distinct advantage for LEMON. While this fact is consistent with previous observations of shortcomings of multilateration techniques, we note two important aspects. First, the advantage of LEMON arguably comes at the cost of a more labor-intensive task of profiling, while an improvement (if any) of the multilateration techniques could come from fitting a more appropriate and representative loss model to the *particular* propagation environment. However, developing a propagation model for a particular environment is likely a labor-intensive task as well. Hence, it is unclear whether a labor-intensive task can be avoided if we seek improved accuracy. Therefore, it is fruitful to consider techniques whereby the profiling (for range-free) or model-fitting (for range-based) is (at least partly) automated.

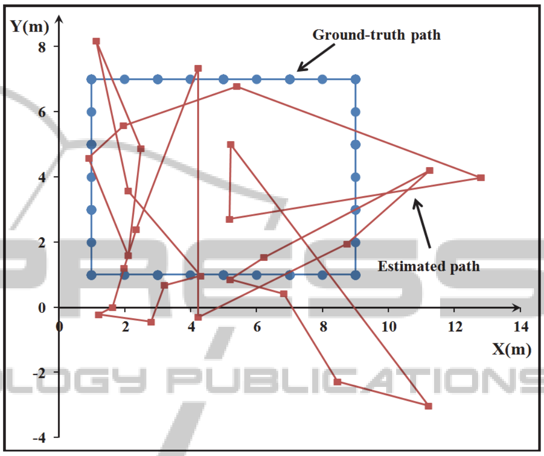

Figure 2: Path (calculated vs. true) using mutlilateration.

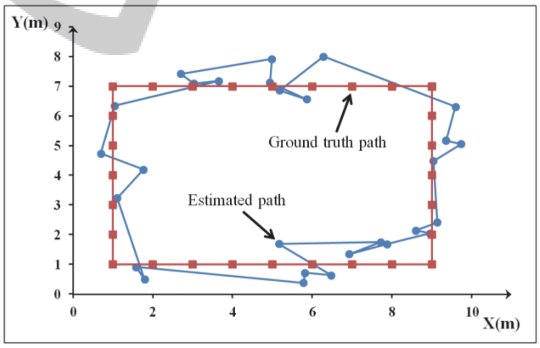

Figure 3: Path (calculated vs. true) using LEMON.

A second observation is the relative "smoothness" of the path in Figure 3. In addition to the average error of the LEMON approach being less than 1.5m compared to more than 4m of the multilateration technique, the standard deviation of LEMON is also much smaller (0.61m vs. 2.4m for mutlilateration). What this suggests is that algorithms that might operate on top of the localization estimates (like, e.g., tracking) are subjected to less variance in their input and could conceivably produce better fidelity results. Hence, another way to see the tradeoff is that cost paid "upfront" for labor-intensive tasks, can pay performance dividends at a higher-level application.

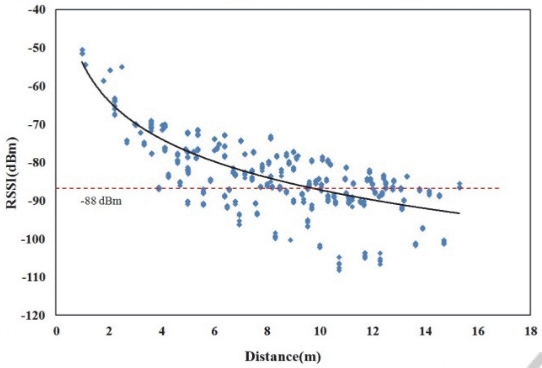

Figure 4: Collected RSSI values.

4 CONCLUSIONS

We observed that localization performance in indoor environments can be improved by utilizing a premeasured map of radio signal strengths. In this case, a set of predefined locations is associated with RSS values (that are sometimes referred to as location “fingerprints. The unknown location can then be estimated online by measuring the signal strength at particular location and searching for the pattern to determine the set of closest matches stored in the database. A weighted average of coordinates of those matches can then be used as an approximate location of the tracked object.

Two aspects requiring further study are the deployment of the pegs and the need to re-profile. Pegs could be incrementally deployed as the structure gets erected, while re-profiling may be needed while the structures change (as they are erected), and hence the RF propagation characteristics change in it. So far we observed from other tests that the changes in the overall RSS map may be relatively, on the average, insignificant with the introduction of cars and humans but some areas are more impacted than others, and hence re-profiling is necessary at least in certain areas. As a starting point, we will exploit the fact that each peg node fixed on a known location could be taken as a profiling reference point as well to assess when re-profiling is warranted.

Our aim is to develop a self-adaptive, self-calibrating, real-time positioning solution based on frequent, dynamic RSS re-profiling. Part of the challenge is how to determine the best placement of pegs, given that there may exist natural restrictions to their placement. Additionally, as can be seen in Figure 4, certain RSS values collected are essentially outliers. While we used all of the collected values in both techniques presented in this paper, one can reasonably argue that certain (especially the lower) values (at the -100dBm mark or less) are outliers and should be eliminated. We plan to develop pre-processing steps to assess the reliability (and outlier elimination) of the measurements before using them for any localization technique.

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