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SELF- CALIBRATED WSN FOR INDOOR TRACKING AND CONTROL OF CONSTRUCTION OPERATIONS

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Abstract: Effective tracking and timely progress reporting are essential for successful delivery of construction projects. In this respect, several research attempts have been made to identify and track the locations of material, equipment and labor on construction Jobsites using wireless sensing technologies. Such developed methods utilize radio signal propagation models to estimate location based on measured received signal strength (RSSI). However, radio signal propagation models are highly dependent on the surrounding environment. As well, these methods are susceptible to interferences caused by metallic structures and obstacles, which are continually changing location on highly dynamic construction jobsites. This paper presents fundamental research work, designed to study the beneficial effect of self-calibrated wireless sensor network (SC-WSN) for higher accuracy of indoor localization. The developed SC-WSN hardware consists of fixed gateway unites mounted at predefined locations and mobile unites mounted on tracked objects. The designed network estimates a tagged object location based on its measured signal strength, which is then converted to corresponding distance using a dynamic signal propagation model. The developed dynamic model calibrates its parameters periodically to minimize errors in its estimated locations using particle swarm optimization algorithm. Experimental results are presented to illustrate the relative effectiveness of the developed system in comparison to commonly used fixed propagation systems.

1 INTRODUCTION

Considerable research work was conducted in recent years embracing the utilization of wireless technologies in construction with a focus on automated project tracking and control. Such application requires frequent location identification of material, equipment and personnel. Despite of the Global positioning system (GPS) success in outdoor localization, it cannot be used indoors due to the lack of satellite's signal coverage inside buildings. A wide range of wireless technologies were utilized for indoor localization on construction jobsites. The fundamental key for reliable and accurate indoor location estimation is signal propagation model, which is used to convert measured received signal strength (RSSI) into corresponding distances. The dynamic nature of construction jobsites severely impacts the accuracy of location estimation. In the presence of moving resources, metallic objects and structural barriers, the signal propagation model produces poor distance estimates. In order to alleviate such impact, smart and adaptive path loss models are required to cope with the fast-changing environment. This paper was motivated with such need for an enhanced localization method incorporating a dynamic signal propagation model, which would increase the accuracy of location estimation.

2 LITERATURE REVIEW

In the construction management domain, several researchers have investigated indoor localization using three main categories of technologies: wave propagation based; image based; and motion based. Several wave propagation based technologies had been utilized by researchers, such as radio frequency identification (RFID), ultra wideband (UWB), wireless local area network (WLAN) and Zigbee. Each technology has its own inherited advantage and disadvantage with relative to accuracy, cost, coverage range, deployment requirements and scalability (Mahalik 2007). RFID had been used for object tracking without localization (Goodrum et al. 2006; Jaselskis et al. 1995) and for tracking with localization (Ergen et al. 2007; Razavi and Moselhi 2012; Montaser and Moselhi 2014). Researches utilizing ultra wideband (UWB) had reported higher localization accuracy of approximately < 1m (Teizer et al. 2007; Rueppel and Stuebbe 2008; Khoury and Kamat 2009; Shahi et al. 2012; Shahi et al. 2013; Vahdatikhaki and Hammad 2014), however the measurement accuracy is highly dependent upon the line of sight of the point to be located (Aryan 2011). WLAN had been seen as an attractive solution for indoor localization due to its existing universal infrastructure availability (Mazuelas et al. 2009). However, several researchers have reported its low accuracy to be approximately 4–7 m with 97% confidence (Khoury and Kamat 2009; Woo et al. 2011).

3 DEVELOPED SYSTEM

The developed system consists of hardware and software implementations. These implementations are designed to meet three main design objectives: accuracy, scalability and cost. The accuracy of the developed system is the main performance measure in comparing it to others. The higher the accuracy, the better the system; however, there is often a trade-off between accuracy and other characteristics such as cost. The accuracy is measured as the average error in location estimation. The scalability of the developed system is required to be applied to any project size without any need for further adjustment or development. Finally the cost of the developed system must be cost effective with respect to others.

4 DEVELOPED SC-WSN HARDWARE

The developed self-calibrating wireless sensor network configuration is a mesh topology with reference tags. The added reference tags, which are fixed at predefined locations, enable self-calibration of the developed system. This self-calibration feature is expected to enhance the performance of the typical mesh topology and provide the intelligence to dynamically adapt the network propagation models to provide optimal localization accuracy. The developed hardware prototype consists of three components: a Waspomote with ATmega1281 microcontroller; a Synapse RF300 radio frequency module and a BMP180 digital barometric pressure sensor. The microcontroller provides a flexibility to custom develop firmware programs for the purpose of indoor localization. The Synapse RF300 radio frequency module has a high indoor coverage range of 250 meters due to its high transmitter power which provides additional 10 dBm of link margin. The BMP180 digital barometric pressure sensor is distinguished by its relatively high accuracy of ±0.12 hPa (±1m), which provides reliable measurements for precise indoor-navigation applications.

Three types of prototypes were developed: tags (mobile tags which are attached to tracked objects and reference tags which are installed at predefined locations); readers; and gateway (where data processing takes place for location estimation and system calibration). Each tag is equipped with a Synapse RF module and barometric pressure sensor as shown in Figure 1a. The RF module is used to estimate the tag's location in 2D space, while the barometric pressure sensor is used to estimate the tag's altitude. The reader node consists of a Synapse RF module, which is programmed to continually scan for nearby tags and report their RSSI value and altitude to the gateway as shown in Figure 1b. The gateway node consists of a microcontroller, Synapse RF module and WLAN module as shown in Figure 1c. It collects data from readers; process the data to estimate tags' locations; calibrates the system and submits the final location data to the database server.

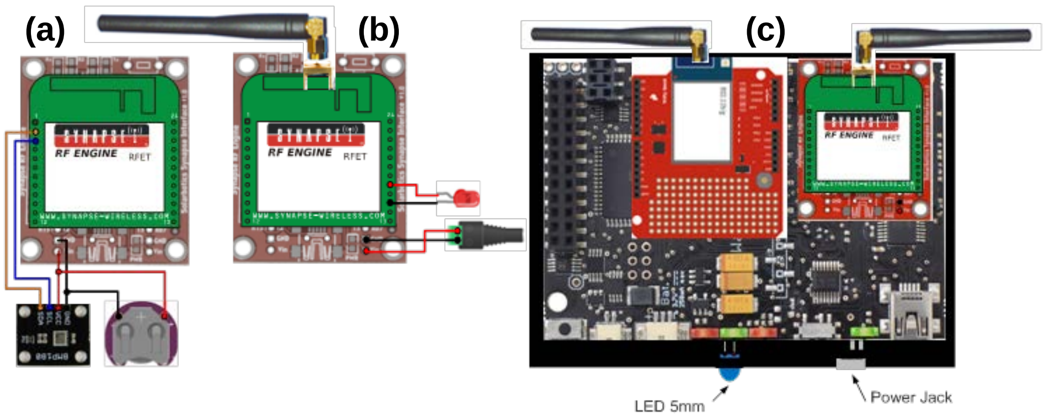

Figure 1: Developed Prototypes: (a) Tag (b) Reader (c) Gateway.

In order to increase accuracy without placing more readers, the system employs the idea of having extra fixed location reference tags to help location calibration. These reference tags serve as reference points in the system.

5 DEVELOPED LOCALIZATION METHOD

The developed method is composed of two stages, prediction stage and calibration stage as shown in Figure 2. Each reader measures the signal strength (RSSI) from nearby tags and filter it to remove uncorrelated noise. Then filtered RSSI data is forwarded to the gateway node for processing. The prediction stage is initiated by converting the filtered RSSI to its corresponding distance using the dynamic signal propagation model. The initial settings for the signal propagation model parameters are calculated using indoor experimentations as explained by Ibrahim and Moselhi (2014). Once three distances from three readers for a given tag are available its location is estimated using the LSE trilateration algorithm. The localization accuracy is continually monitored by measuring the errors in location estimation generated based on a number of reference tags. These reference tags are deployed on site at pre-defined locations. When the system accuracy is degraded due to on-site interferences, a system calibration request is initialized. The user can define the accuracy limits to initiate the calibration requests. The calibration stage utilizes a particle swarm optimization (PSO) to find the best values for the signal propagation model parameters which maximize the system localization accuracy. Finally, at the end of the calibration stage, the dynamic signal propagation model is updated with the new set of optimized parameters.

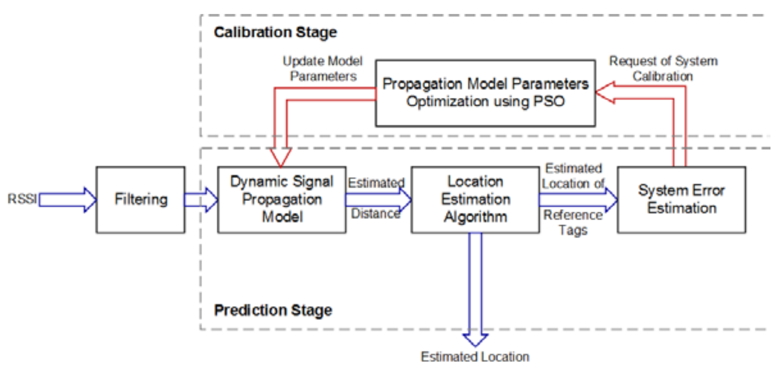

Figure 2: Developed Localization Method Overview

5.1 Signal Propagation Model

A propagation model is a set of mathematical expressions used to represent the radio characteristics of a given environment (Neskovic et al. 2000). The signal propagation model used in this research is Log-distance Path Loss Model. The path loss PL (d) for a transmitter and a receiver with distance d is:

[1] $PL(d) \propto \left(\frac{d}{d_0}\right)^n$

[2] $PL(dB) = PL(d_0) + 10\, n\, ln\left(\frac{d}{d_0}\right) + \sigma^2$

Where n is the path loss exponent which indicates the rate at which path loss increases with distance d. The reference distance (d_0) is determined from measurements at 1 meter distance from the transmitter. σ^2 is the shadowing variance in mdB. The value of n depends on the specific propagation environment, i.e., type of construction material, architecture, location within building. Table 1 lists typical path loss exponents obtained in various radio environments (Rappaport 1996).

Table 1: Path loss exponents for different environments (Rappaport 1996)

Environment	Path Loss Exponent, n
Free Space	2
Urban area cellular radio	2.7 to 3.5
Shadowed urban cellular radio	3 to 5
In building line-of sight	1.6 to 1.8
Obstructed in buildings	4 to 6
Obstructed in factories	2 to 3

Given that d_0 = 1 m, equation 2 can be simplified as:

[3] $PL(dB) = A + B\, ln(d)$

Where A & B are the parameters for the signal propagation model. The signal propagation model parameters (A&B) are estimated using lab experiments, then automatically adjusted on-site using the PSO.

5.2 Location Estimation Algorithm

Based on RSSI measurement and signal propagation model described above, the multilateration (Karl and Willig 2007) algorithm is used to calculate tag's location based on its estimated distance from a set of fixed readers (Stüber and Caffrey 1999). When three readers are used, it is called trilateration, as shown in Figure 3a. The intersection of the three circles gives an exact solution for the tag's location under ideal free space signal propagation (no fading or shadowing effect). However, in real environment, the three circles might not even intersect due to errors in distance estimates by RSSI propagation model. Stuber and Caffrey 1999 presented an optimal localization using least square estimation (LSE) as shown in Figure 3b.

Given the readers coordinates as following: A(x_1, y_1), B(x_2, y_2), and C(x_3, y_3); and their corresponding distances to the tag are d1, d2, and d3; the three circles equations can be formatted as follows:

[4] $(x_1 - x)^2 + (y_1 - y)^2 = d_1^2$

[5] $(x_2 - x)^2 + (y_2 - y)^2 = d_2^2$

[6] $(x_3 - x)^2 + (y_3 - y)^2 = d_3^2$

Where x and y are the coordinates for the tag location.

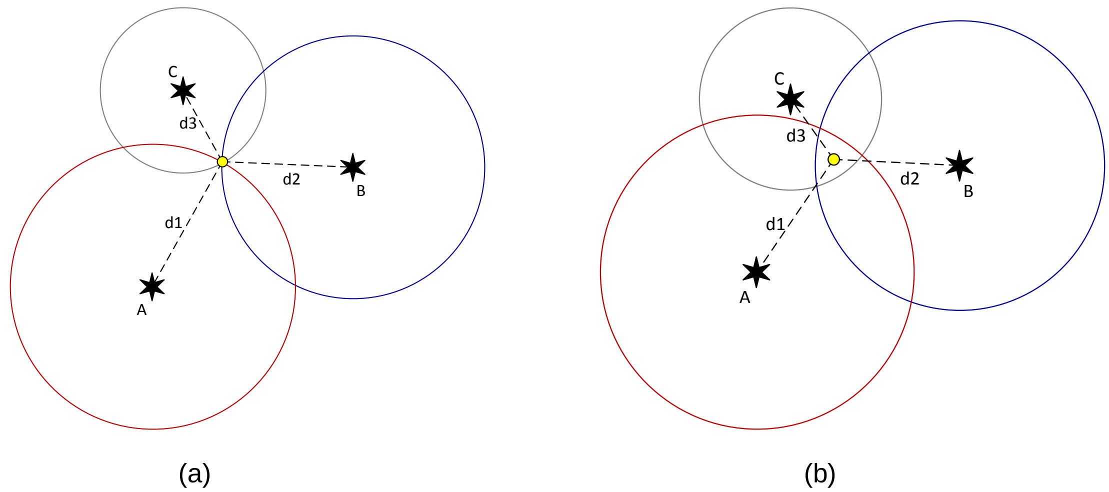

Figure 3. Localization using Trilateration

Using the LSE method the tag coordinates can be calculated using the following equation:

[7] $2 \cdot \begin{bmatrix} x_3 - x_1 & y_3 - y_1 \\ x_3 - x_2 & y_3 - y_2 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} (d_1^2 - d_3^2) - (x_1^2 - x_3^2) - (y_1^2 - y_3^2) \\ (d_2^2 - d_3^2) - (x_2^2 - x_3^2) - (y_2^2 - y_3^2) \end{bmatrix}$

5.3 System Accuracy Estimation

Localization system's accuracy depends mainly on the accuracy of the estimated tag's distances from the fixed readers. It can be measured in terms of Euclidian distance error between the estimated location and the actual location. The location's error is calculated as the distance in meters between the estimated and actual locations using Eq. 8.

[8] $Distance_{error} = \sqrt{(X-a)^2 + (Y-b)^2}$

Where: (X, Y) is the actual tag location, and (a, b) is the estimated tag location.

The optimization algorithm described later is designed to find a near optimum solution for propagation model parameters in order to maximize its localization accuracy. However, using the Euclidian distance error as an objective function for the optimization algorithm increases required computational overheads by the microcontroller. Therefore, the error in the distance estimation (between a reader and a reference tag) is used to measure the system accuracy. Hence it was important to study and understand the sensitivity of the estimated distance on the location calculation using the LSE trilateration algorithm described above.

Monte-Carlo simulation is used to study the LSE trilateration algorithm sensitivity to the estimated distances. This simulation is used to quantify the effect of estimated distance errors on the estimated tag's location. The identified sensitivity thresholds (limits) will be used to flag requests for localization system calibrations. To perform this sensitivity analysis; three fixed readers were placed at locations (0, 0), (0, 3) and (5, 3). A tag was placed at the location (2.5, 1.5), and its estimated distances were ranged to show four levels of error (±5%, ±10%, ±15%, ±20%). Figure 4 shows the tag's estimated location against the tag's actual location.

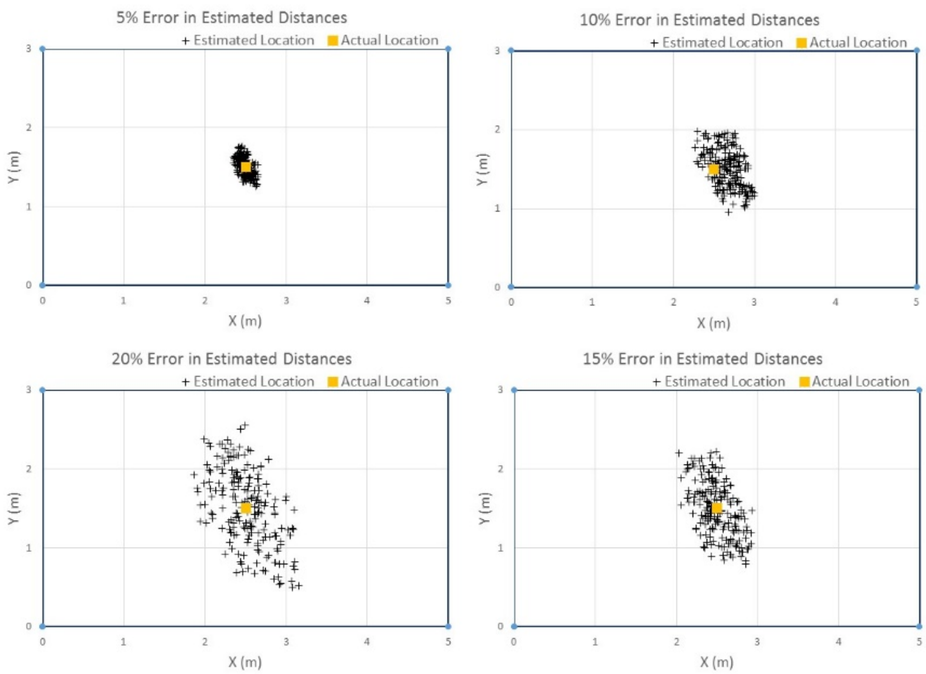

Figure 4. Tag's Estimated Locations vs Actual Location

The empirical CDF of the estimated location errors was calculated to derive the thresholds for the system accuracy with 95-percentile confidence level as shown in Figure 5 and Table 2.

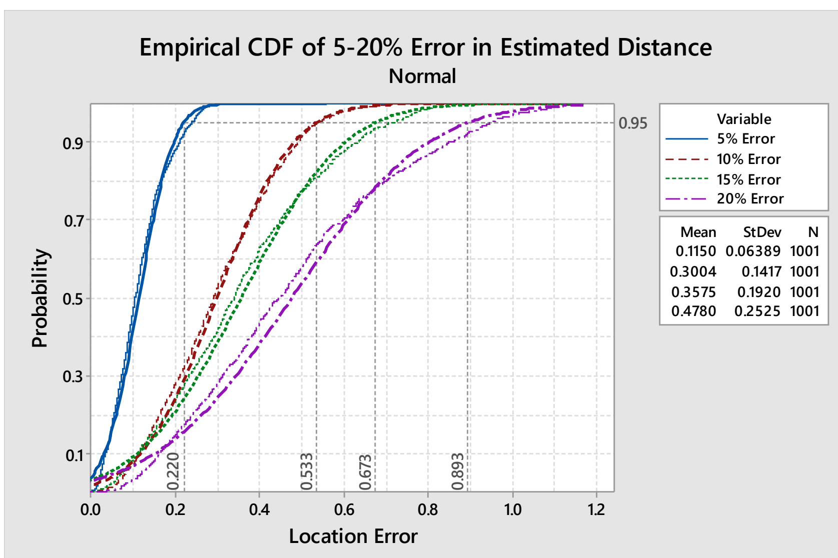

Figure 5. The CDF of Tag's Estimated Location Errors

Table 2: Location Estimation Error Thresholds vs Errors in Distance Estimation

	Error in Distance Estimation			
	±5%	±10%	±15%	±20%
Location Estimation Error (m)	0.220	0.533	0.673	0.893

The developed system was designed to trigger system calibration when the error in distance estimation becomes higher than ±15% in order to keep the location error within 0.65 meters (however these settings are changeable by the user).

5.4 Propagation Model Self-Calibration

The developed calibration process is intended to automatically derive propagation parameters without any prior knowledge on propagation conditions. It relies on periodic calculation of reference tags locations and computation of system accuracy, and then auto calibrate the model parameters when experienced low accuracy conditions.

From equation 3, the measured distance $d_{measured}$ can be calculated as:

[9] $$d_{measured} = e^{\left(\frac{PL(dB)-A}{B}\right)}$$

The absolute error d_{error} in the measured distance can be calculated as:

[10] $$|d_{error}| = |d_{actual} - d_{measured}| = \left|d_{actual} - e^{\left(\frac{PL(dB)-A}{B}\right)}\right|$$

Where is the actual distance d_{actual}.

The Average Absolute distance error for m readings collected from readers:

[11] $$\overline{|d_{error}|} = \frac{1}{m}\sum_{i=1}^{m}\left|d_{actual_i} - e^{\left(\frac{PL(dB)_i-A}{B}\right)}\right|$$

The calibration algorithm will determine the value of A and B to minimize the mean absolute error for each reader. The objective function of the algorithm is:

[12] $$Z = min\left(\frac{1}{m}\sum_{i=1}^{m}\left|d_{actual_i} - e^{\left(\frac{PL(dB)_i-A}{\mathrm{B}}\right)}\right|\right)$$

This objective function is non-linear which does not allow for an exact solution. Evolutionary optimization methods such as Genetic Algorithm (GA) or Particle Swarm Optimization (PSO) can be used to solve these kind of problems. PSO has the same effectiveness (finding the true global optimal solution) as the GA but with significantly better computational efficiency (Hassan et al. 2005). The computational efficiency of the selected optimization algorithm is very important for the developed method due to the limited computational resources of the microcontroller (memory and speed).

6 EXPERIMENTAL VALIDATION

For validating the proposed method, experiments were conducted using a grid formation test bed, where readers are installed at the corners of the area, then tags were placed one meter apart in grid formation as shown in Figure 6a. This test setup is repeated after adding physical obstacles in the surrounding environment (as shown in Figure 6b) to simulate the change in the environment and test how the proposed method self-calibrates its model to account for interferences caused by the surrounding environment. Experiments were conducted in a laboratory environment at Concordia University Construction Automation Lab. A total of 1062 data sets were collected covering 15 m^2 of surface area. The test bed had 17 mobile tags, 4 reference tags and 3 fixed readers, with an average density of one reader per 5 m^2 and one reference tag per 3.75 m^2. In the first experimental step the setup in Figure 6a was used and the dynamic signal propagation model (Eq. 3) has been initialized with initial values based on experimental measurements (A= -38.909 and B= -8.989) and tags' distances from the fixed readers were estimated accordingly. The system localization accuracy was measured at 87%.

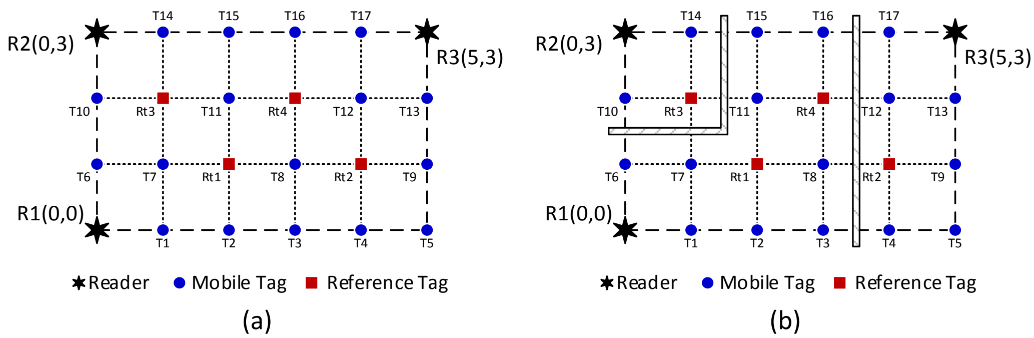

Figure 6. Grid Formation Test Bed

After adding physical obstacles as shown in Figure 6b, the system location accuracy fall below 80% and the distance error were increased. Figure 7 shows a graphical display of the actual locations verses the estimated tag's locations after adding the obstacles, the orange triangles represent the actual tag's locations, and the black crosses represent the calculated tag's location.

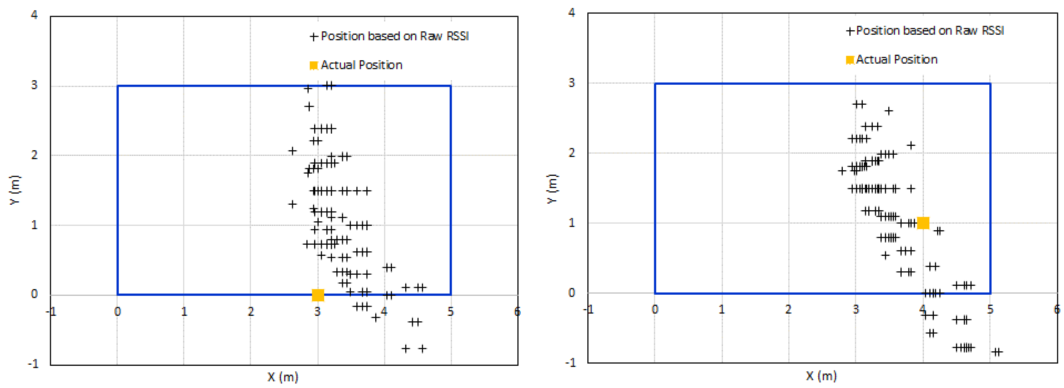

Figure 7. Graphical Representation of Actual vs Estimated Tag's Locations before calibration stage

The calibration stage was initiated based on encountering low system accuracy. Each reader signal propagation model is optimized using PSO algorithm and the RSSI from reference tags, the enhancement in the location estimation is clearly identified in Figure 8, which shows a graphical display of actual tag's locations verses the estimated tag's location after calibration.

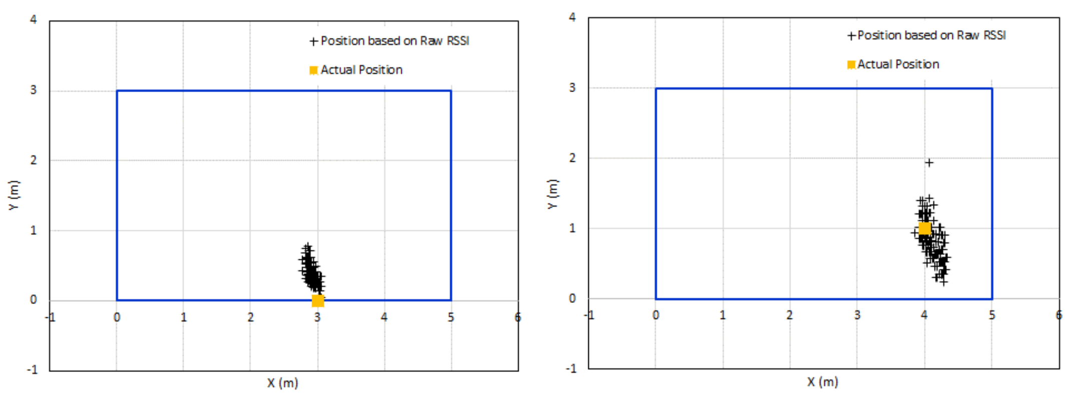

Figure 8. Graphical Representation of Actual vs Estimated Tag's Locations after calibration stage

Figure 9 shows the CDF of estimated distance errors for reader 1 before and after the calibration stage, where the mean error in the distance shows a decreasing trend. The mean absolute percentage error before calibration was 37.69%, while it was 14.96% after calibration. The SC-WSN method decreased the mean absolute percentage error by 60%.

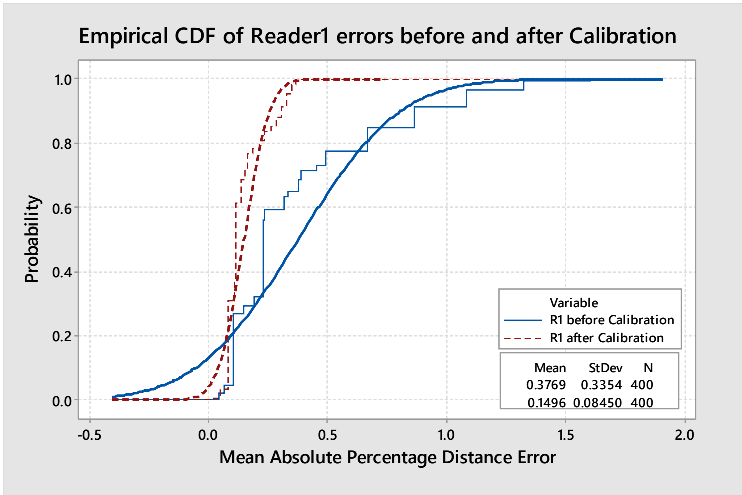

Figure 9. CDF of Estimated Distance Errors for Reader 1 before and after Calibration

It is important to mention that from a practical deployment point of view, an in-depth analysis about the relationship between the density of reference tags and their geometrical distribution needs further investigation. Also, it is important to investigate the processing time for the proposed method with respect to its real time applications. These issues are part of this ongoing research.

7 CONCLUSION

This paper presented a newly developed method for indoor localization on dynamic construction jobsites utilizing a self-calibrated wireless sensor network (SC-WSN). The developed SC-WSN hardware consists of fixed gateway unites mounted at predefined locations, reference tags and mobile tags mounted on tracked objects. The developed method consists of a prediction stage and calibration stage. The prediction stage estimates the tag's location based on its measured signal strength (RSSI), which in turn is converted to the corresponding distance from fixed readers by a dynamic signal propagation model. The calibration stage is executed whenever the system accuracy falls below 80%, where the dynamic propagation model parameters are optimized to minimize the distance estimation errors of the reference tags. A particle swarm optimization (PSO) algorithm is used to find a near optimum solution for this non-linear problem. The PSO is not only able to find a solution effectively, but also has significantly better computational efficiency. Experimental results illustrated the significant accuracy improvement in estimating locations on construction jobsites, where the mean absolute percentage error before calibration was 37.69% while it was 14.96% after calibration. The SC-WSN method decreased the mean absolute percentage error by 60%.

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