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Comparative evaluation of Received Signal-Strength Index (RSSI) based indoor localization techniques for construction jobsites

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ABSTRACT

This paper evaluates the accuracy of several RSSI-based localization techniques on a live jobsite and compares them to results obtained in an operating building. RSSI-based localization algorithms were tested due to their relative low cost and potential for accuracy. Four different localization algorithms (MinMax, Maximum Likelihood, Ring Overlapping Circle RSSI and *k*-Nearest Neighbor) were evaluated at both locations. The results indicate that the tested localization algorithms performed less well on the construction jobsite than they did in the operating building. The simple MinMax algorithm has better performance than other algorithms, with average errors as low as 1.2 m with a beacon density of 0.186/m^2. The Ring Overlapping Circle RSSI algorithm was also shown to have good results and avoids implementation difficulties of other algorithms. *k*-Nearest Neighbor algorithms, previously explored by other construction researchers, have good accuracy in some test cases but may be particularly sensitive to beacon positioning.

1. Introduction

Knowing the location of people, equipment, and materials is important information for various construction activities such as safety management, material management, and production planning. Accurate and reliable location information can lead to better decision making [1]. To address the demand for location awareness in construction applications, many researchers have investigated various localization techniques, such as global positioning systems (GPS), radio frequency identification (RFID), and laser scanning [2–4]. Much of this research pertains to location in outdoor environments. To obtain location information for construction management tasks in indoor working environments an accurate and fast location estimation process is required. Although different techniques for indoor localization in construction have been proposed [1,5], few of them have been tested and validated in live construction environments. Such a test is important as the jobsite and operating building present different environmental conditions. In particular, an operating building may have relatively more electronic interference from operating computers and wireless emitters, whereas a jobsite may have more exposed metals such as ductwork for reflectivity.

The research introduced in this paper aims to evaluate the technical performance of several relatively low-cost and easily expandable RF-based localization techniques on a live construction site. To evaluate their performance, the authors set up two test beds, one in a live construction jobsite and the other with similar characteristics in an operating building for comparison. In both test beds, several beacon nodes were suspended from the ceiling, and a tablet equipped with mounted receiver was placed in preselected positions on the floor to collect Received Signal-Strength Index (RSSI) values from beacons. With the collected data, the authors conducted the location estimation by using four RSSI-based localization algorithms and comparing their accuracy in both environments. This research expands previous results which have primarily investigated one algorithm (*k*NN) and have limited exploration to operating buildings rather than live jobsites.

2. Literature review

Localization techniques have been deployed in other industries and military applications [2,6]. More recently, these techniques have been evaluated and developed for use in the construction industry. An early construction application is the use of GPS for on-site material tracking [7]. However, GPS is not yet widely adopted by construction practitioners due to the following limitations: first, although GPS receivers are relatively inexpensive, deploying GPS devices on all equipment, tools, laborers and batches of material that require location information on site can still sum up to a large investment. Second, the accuracy of existing handheld GPS devices is not satisfactory for many construction applications. General-purpose GPS has an accuracy of about 10- to 20-m, while other more expensive and advanced GPS systems

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(e.g., Nationwide Differential GPS) might have accuracy of 1 to 2-m [8,9]. Third, the primary drawback of GPS is that it does not work indoors. Despite the aforementioned shortcomings, GPS is still useful for onsite material tracking and other applications, where applications are mostly outdoors and do not have a strict requirement for accuracy.

To overcome the limitations of GPS, technologies such as laser scanning and RFID have been evaluated for use in outdoor construction. Laser scanners are deployed on vehicles to detect the location information of surrounding objects to prevent collisions [10]. However, there are two major disadvantages of laser scanning: high resource utilization (time, CPU and memory) in real time applications, and, more generally, requirement for line-of-sight imaging. Another device commonly seen on construction jobsites is RFID tags, used for material management [4,11]. RFID tags are attached to material stacks, so as to collect radio signal data to estimate the target's location when the RFID reader moves around the jobsite. Several localization techniques have been proposed using RFID tags, and some have achieved accuracy of as little as 3.2 m [11].

While outdoor localization techniques have been developed and deployed, indoor methods remain a research challenge [12]. There are five technical approaches that may be applied to indoor localization: indoor GPS, ultrasonic localization, infrared, computer vision, and radio frequency (RF) based technologies, including time-of-arrival (TOA) and received signal-strength index (RSSI) [13–16]. We briefly describe each technology with a more thorough review of the RF methods evaluated in this paper.

Indoor GPS is similar to outdoor methods, although satellites are augmented with local equipment. Several signal transmission base stations are mounted in known locations and emit signals at a preset frequency. Usually when the GPS receiver gets signals from two or more transmitters, it can determine its location through triangulation. Although the indoor GPS can achieve high localization accuracy, it is costly and requires line-of-sight [15,17].

Ultrasonic systems, such as the Cricket localization system, use a combination of RF and ultrasonic techniques to estimate the location information of the host device [18]. In this system, an ultrasonic pulse is transmitted by the beacon concurrently with a RF signal. The host device can estimate the distance by using the speed difference between RF and ultrasonic waves. Using the distance between the host device and multiple transmitters, the location of the host device can be determined by localization algorithms such as trilateration. However, because the system's performance is sensitive to temperature variance and multipath signals [16], it is not suitable for most construction jobsite indoor applications since jobsite temperature varies during the day. Enclosed jobsites with environmental controls may be candidates for ultrasound and further investigation for these specialized applications is warranted.

Infrared systems are common in commercial applications for inventory tracking. An early application is described by Want and his colleagues who used an 'Active Badge' that emitted an infrared signal that was read by fixed sensors with known locations [19]. The location of the mobile badge is tied to the sensor that reads it. Such systems are utilized for inventory management in rooms where the degree of accuracy needed is at the room level.

In the past two decades, various vision-based localization systems were developed and applied, for example, in mobile robotics [20]. The robot software uses onboard cameras to capture real time images, extracts several features from the images and estimates location by using matching models. An alternate approach is to mount multiple cameras at different viewpoints to get images containing the target object and to estimate its location using various image processing algorithms [21,22]. However, the localization performance of these algorithms is very sensitive to the camera characteristics such as blur, noise and frame rate. The multiple-camera tracking system was introduced for construction equipment and workforce tracking on site [14,23], although several challenges remain before functional deployment – not least of them is overcoming line-of-sight requirements in indoor environments.

Of techniques that use radio-frequency to measure location, time-of-arrival (TOA) techniques have shown great promise. In particular, ultra-wideband (UWB) TOA algorithms have shown to have indoor performance with precision of tens of centimeters [12,24]. However, this performance requires a direct path between sensors, giving a limitation similar to line-of-sight requirements. Recent advances have allowed the direct path constraint to be relaxed, although performance degrades [13]. More broadly, UWB-based systems have a higher deployment cost than other RF techniques due to the need for high sampling rates and precise inter-node time synchronization; such systems are also less robust due to problems with interference and need for high signal reliability [24,25].

Due to limitation of the previously described approaches, recent construction research has investigated the use of RF technologies that measure the strength of the received signal [11,26]. Such RF-based technologies assume that there are some transmitting nodes with known spatial location and act as beacon points to localize other nodes with unknown location. There are two primary families of RF based algorithms: range-free and range-based. Range-free assumes no prior knowledge about RSSI signal strength whereas range-based utilizes an initial calibration for beacon signal strength and location. Range-based algorithms are further divided into several categories, the principal ones being RSSI map-based and path-loss model-based algorithms. These are described below in more detail.

2.1. Range-free algorithm: Ring Overlapping Circle RSSI (ROCRSSI)

This algorithm uses the concept of relative signal strength loss with distance to estimate location of a target node [27]. Suppose there are a set of beacon nodes with known location and, for simplicity, one target node. Each beacon node reads the signal strength from the other beacon nodes and from the target node. For a given beacon node, there will be a set of signals from the target node and the other beacon nodes. These are ordered by signal strength and the beacon node readings are divided into two groups: group 1 with RSSI values not greater than the RSSI value read from the target node and group 2 with all other RSSI values greater than the target node. Because the algorithm presumes that distance is a function of signal strength, the maximum RSSI value in group 1 is presumed to give a distance that is close to the target node, defining an inner ring of radius $R1$. $R1$ is the distance between the beacon nodes. Similarly, the minimum RSSI value in group 2 is presumed to give a distance close to the target node, defining an outer ring of radius $R2$. $R2$ is the distance between the corresponding beacon nodes. The rings defined by $R1$ and $R2$ provide and upper and lower bound for distance from the beacon node. Repeated for all the beacon nodes, a set of overlapping ring pairs are created. The target node is located as the center of gravity of these overlapping ring pairs.

Fig. 1 gives an example to illustrate the method. Beacon A reads the RSSI values from T, B, C as $RSST_{AT}$ $RSST_{AB}$ and $RSST_{AC}$. The readings show that $RSST_{AB} < RSST_{AT} < RSST_{AC}$. B and C can be divided into two groups: group 1 with B and group 2 with C. Since group 1 only has one beacon node, the maximum RSSI value is $RSST_{AB}$ and the distance between A and B is $R1$ shown in the figure. Similarly, $R2$ is the distance between A and C. Then T is assumed to sit in the ring area between two circles centered at A with radius of $R1$ and $R2$. Repeating the same procedure for B and C, we can

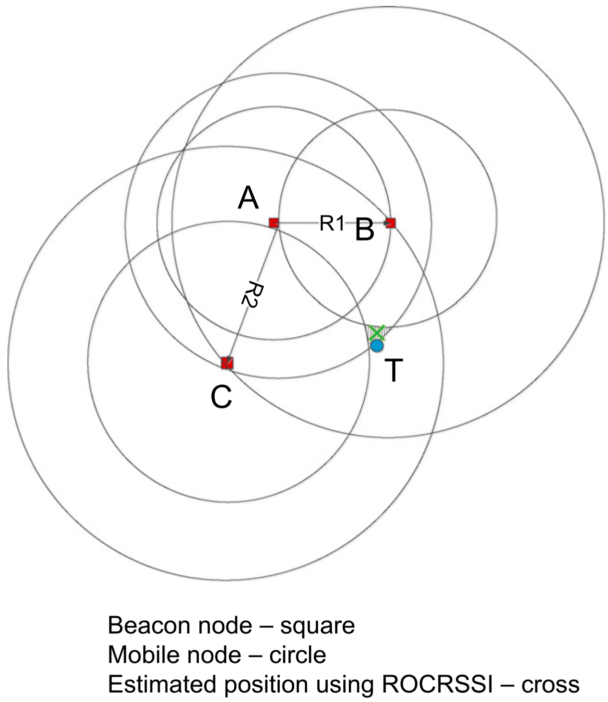

Fig. 1. ROCRSSI algorithm.

intersect the rings of circles and conclude that the target node sits in the gravity center of the shadow area in Fig. 1.

2.2. Path-loss model-based algorithms

The foundation of these algorithms is path loss regression model. It is calibrated using a set of RSSI values collected at various known sampled points to determine the relationship between RSSI values and the distance from the transmitting node to the receiving node. A regression equation model of this relationship is constructed and used to estimate the distances based on RSSI values and the target's location. Based on the path loss, there are many algorithms for location estimation based on the RSSI value or calculated distances. We present three commonly used algorithms:

- Trilateration: the principle of trilateration is that knowing the distances between the target node and three nodes with known location information, the target node's 2D location can be determined; knowing the distance between the target node and four nodes with known location information, the target node's 3D location can be determined. An application of this algorithm is SpotON [28]. A significant disadvantage of this algorithm is that it is resource intensive to implement [29].
- MinMax: in the MinMax algorithm, each beacon node measures the RSSI value from the target node and calculates its distance d to target node using the RSSI value based on the path-loss model. Then a square with width of $2d$ is drawn around the beacon node [30]. The target node lies within the overlapping area of all of the squares drawn around all beacon nodes (Fig. 2). This algorithm is very easy to implement but may have some increase in error as the algorithm uses a bounding box rather than circle, giving a wider area measured from each beacon [30].
- Maximum Likelihood: this algorithm is based on classical statistical inference theory [31]. Given the location of each beacon node and the distance from it to the target node, the maximum likelihood algorithm maximizes the probability of the target node's calculated location by minimizing the variance of estimated error. However, the performance is sensitive to the number of beacon nodes [32].

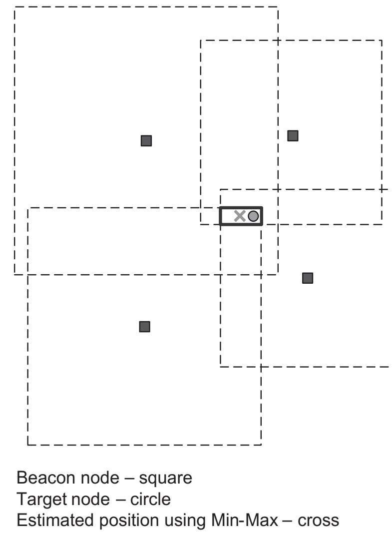

Fig. 2. MinMax algorithm.

2.3. RSSI map-based algorithms

In RSSI map-based algorithms, a target node matches sampled points on the RSSI map, which records the RSSI values of beacons at different sampled points with the closest RSSI values to the target. A typical method using RSSI mapping is the k-nearest neighbor (kNN) training based algorithm [33]. In the kNN algorithm, a data set of beacon node RSSI values at different sample points is used to train the algorithm and to get the RSSI signature map. The training data set with n beacon nodes is stored in an n-dimension space. Given a target position's RSSI values read from the beacons, the system searches the training data set to find the k nearest matching data records, so as to determine the target position's location information using the k data records. Closeness (or proximity) is defined in Euclidian distance which is calculated by using the following equation (Eq. (1)):

$$D_t \sqrt{\sum_{j=0}^{N} (\mathrm{RSSI}_{tj} - \mathrm{RSSI}_{\text{test point}-j})^2} \tag{1}$$

In Eq. (1), RSSI_{tj} is the RSSI value read from beacon j at location t and $\mathrm{RSSI}_{\text{test point}-j}$ is the RSSI value read from beacon j at the target position. The unit of D_t is dbm, which is the decibels (dB) of the measured power referenced to one milliwatt (mW). There are several existing indoor localization systems using the kNN algorithm: RADAR based on 802.11 Wifi Technology [33], LANDMARC [34] as well as Ekahau real time location system (RTLS) tested in indoor construction [35]. The best accuracy of Ekahau RTLS in an indoor building is 1.5–2 m [17].

2.4. Research objectives and methodology

RF based methods show promise for construction utilization as they are relatively inexpensive to deploy and are less subject to the line-of-sight limitations that affect many other methods. Some research has been done evaluating the use of RF methods in construction, but these have primarily focused on evaluations within existing buildings. This research investigates performance of RF-based localization techniques in a live indoor construction jobsite as well as in an operating building. By comparing performance on a construction jobsite to that in an operating indoor environment, the authors hope to offer other researchers a better understanding of the potential for applying existing indoor localization algorithms in construction as well as provide guidance for future research in localization and associated efforts such as route planning. As there are many factors that influence performance, the goal of this research is not to conduct an exhaustive evaluation but rather to add to the existing literature by evaluating algorithms other than *k*NN and also to evaluate performance on a live jobsite. The limited, specific research objectives are twofold: first, evaluate the comparative performance of selected algorithms against the *k*NN map based algorithm. Second, investigate performance variations between deployment on a live jobsite and an operating building to help assess potential issues with using operating buildings as surrogates for construction jobsites.

The four methods (MinMax, Maximum Likelihood, ROCRSSI and *k*NN) discussed in the last section are the primary ones in RF based method category. Trilateration is not considered here because it has an accuracy performance comparable to the one of MinMax but it is more costly than MinMax regarding ease of implementation, running time and storage space requirements [29]. Past research uses the cumulative distribution function (CDF) of localization error as well as basic statistical metrics (mean value, average value and standard deviation) of localization error to measure the localization performance [36–38]. The CDF $F(e)$ of localization error e is defined in term of a probability density function $f(e)$ as follows (Eq. (2)):

$$F(e) = \int_0^e f(x)dx \quad (x \geqslant 0) \tag{2}$$

From the CDF of localization error, we can tell the localization error at a given confidence level (e.g., 50%, 97%). Computing performance is not covered in our research since the setting does not affect algorithmic complexity and other research addresses performance [24,32].

The equipment used for the readings were Crossbow Technologies Mote 2 (mote) devices. Each mote, equipped with an integrated sensor board, is programmed to broadcast a short data package with a unique ID to other mote nodes within 1 hop distance. The standard frequency is 900 MHz, which is typical of other tests [39]. Another mote (as receiver) on the programming board (MIB520) is attached to a tablet computer and programmed to catch the available data packages sent by transmitter nodes. When the receiver gets a data package, it decrypts the message and writes the RSSI value with corresponding sender's ID into the data log.

Previous research indicates that beacon node density affects localization error [31,36,38]. To validate this on the construction jobsite, we chose two areas with comparable sizes, one in a live jobsite and the other one in an operating building. Both test beds are located near the corner of the floor and have an area comparable in size and beacon density to that performed in previous studies [31,37,38] to facilitate comparison. To avoid the potential for strong reflection and multipath effects from the floor and ceiling, we kept the beacons and target sensors away from hard surfaces (see details below). This setup is representative of the use of RF to track people and pallets of materials, although it is not true for installed materials. Our efforts made these two test beds comparable by having them similar in all factors but the characteristic difference between a live jobsite and an operating building.

The first test bed was located in a classroom (Fig. 3) of 7.0 m in width and 6.4 m in length on the 5th floor of a major building on the University of Texas at Austin campus. This area is comparable to the live construction site test bed (described below). On the floor four motes were deployed as beacon nodes in the grid and suspended at a distance of 0.61 m away from the ceiling. The closest distance between any two beacons was 3.0 m and the furthest distance was 4.8 m. The average beacon density was 0.089 beacon nodes per square meter. Twenty-one sampled locations were marked on the floor with their location information recorded. RSSI values from beacons were collected at each sampled location while the receiver was mounted on a tripod at a height of 1.04 m away from the floor (Fig. 4). The authors collected over 2000 readings at each sampled location.

Fig. 3. Test bed #1.

The second test bed was located in a corner of the 40th floor in a high rise residential building under construction in downtown Austin, Texas. The floor was enclosed with a combination of exterior glass walls and concrete walls and had no interior walls or frames erected. Data collection was concurrent with active construction on the floor, including HVAC installation and piping. We note that active construction limited the area available to the researchers for evaluation. Within constraints, a target area of 6.3 m by 5.1 m on the floor was chosen as the test bed. Six motes were deployed as beacon nodes in the grid (Fig. 5) and suspended

Fig. 4. Receiver mounted on tripod.

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Fig. 5. Test bed #2.

at a distance of 0.6 m away from the ceiling. The closest distance between any two beacons was 1.03 m and the furthest distance was 3.43 m. The average beacon density was 0.186 beacon nodes per square meter, twice as much as that in test bed 1. Eighteen sampled locations were marked on the floor for collection of RSSI values. Table 1 summarized the characteristics of the two test beds.

Since test bed #2's beacon density is twice as much as test bed #1's, we extended test bed #2 to test bed #3 by using only 3 beacons out of the 6 deployed on test bed #2 and making test bed #3's beacon density roughly the same as test bed #1. This allows comparison at different beacon densities within the same test bed as well as improving comparison with the operating building testbed (#1).

3. Findings

This section describes the research findings for the path-loss models and map-based algorithms.

3.1. Range-free and path-loss model-based analysis

MinMax and ML models require a path loss function. For an initial calibration, using the log-linear regression model, the parameters in the path-loss model were calculated as (Eqs. (3) and (4)):

$$\text{Test bed}\#1 : \text{RSSI} = -5.93105\ln(d) - 42.9329 \qquad (3)$$

$$\text{Test beds}\#2\ \&\ \#3 : \text{RSSI} = -8.39668\ln(d) - 29.6844 \qquad (4)$$

where RSSI was measured in power ratio dBm. The distance, d, between the beacon node and the receiver node was measured in inches.

For each entry of the collected data at target position, the ML, MinMax and ROCRSSI algorithms were used to estimate the location and compare it with its true value for error assessment. Table 2 summarizes the performance of the three localization algorithms. In all three test beds, the MinMax algorithm had better performance (Average Error, Median Error and Standard Deviation) than the ROCRSSI and ML algorithms. Table 2 shows values for all readings in the testbed; there are differences in average error across different nodes, but these differences do not follow a stable or geometric pattern (e.g., a pattern that shows better readings inside a ring of beacon nodes as opposed to the edge of the testbed).

To obtain a better sense of the consistency of localization readings, Fig. 6a and c show the cumulative probability function (CPF) of the three different algorithms' estimation error on test beds #1, #2 and #3, respectively. All three figures show that the MinMax algorithm outperforms Maximum Likelihood and ROCRSSI algorithms. More specifically, the estimation error of MinMax algorithm is less than those of ROCRSSI and Maximum Likelihood algorithms at both 50% and 90% confidence levels. In Fig. 6c, it shows that the MinMax algorithm's estimation error is less than those of Maximum likelihood and ROCRSSI at 50% confidence level while it is slightly larger than that of ROCRSSI algorithm at 90% confidence level.

Comparing Fig. 6b and c, the performance of each of these three algorithms decrease while the beacon density decreases (no change to other environmental parameters). This result is also shown in the data from Table 2. While only two beacon densities were evaluated at this location, these results are consistent with other literature showing an increase in accuracy with density [36,40].

Fig. 7a and c compares estimation error on the construction jobsite and in the operating building for each of the algorithms, using comparable area size and beacon density (testbeds #1 and #3). The figure shows that the performances of these algorithms are better in an operating building than those on a construction jobsite regarding the median estimation error. When we examine the estimation error at 90% confidence level, the path-loss based algo-

Table 1
Comparison of two test beds.

#	Type	Test point #	Area/m^2	Beacon #	D_{min}/m	D_{max}/m	Beacon Density(#/m^2)
1	Building	21	44.87	4	3.04	4.76	0.089
2	Jobsite	18	32.26	6	1.04	3.43	0.186
3	Jobsite	18	32.26	3	1.54	3.10	0.093

Table 2
Performance comparison of three localization algorithms (error in meters).

Testbed	MinMax			ROCRSSI			Maximum Likelihood		
	Average	Median	SD	Average	Median	SD	Average	Median	SD
#1	1.55	1.38	0.73	2.18	2.05	1.31	3.11	3.18	1.56
#2	1.22	1.26	0.39	1.69	1.52	0.83	2.52	2.66	0.92
#3	2.58	2.06	1.15	2.76	3.13	1.11	3.79	3.68	1.57

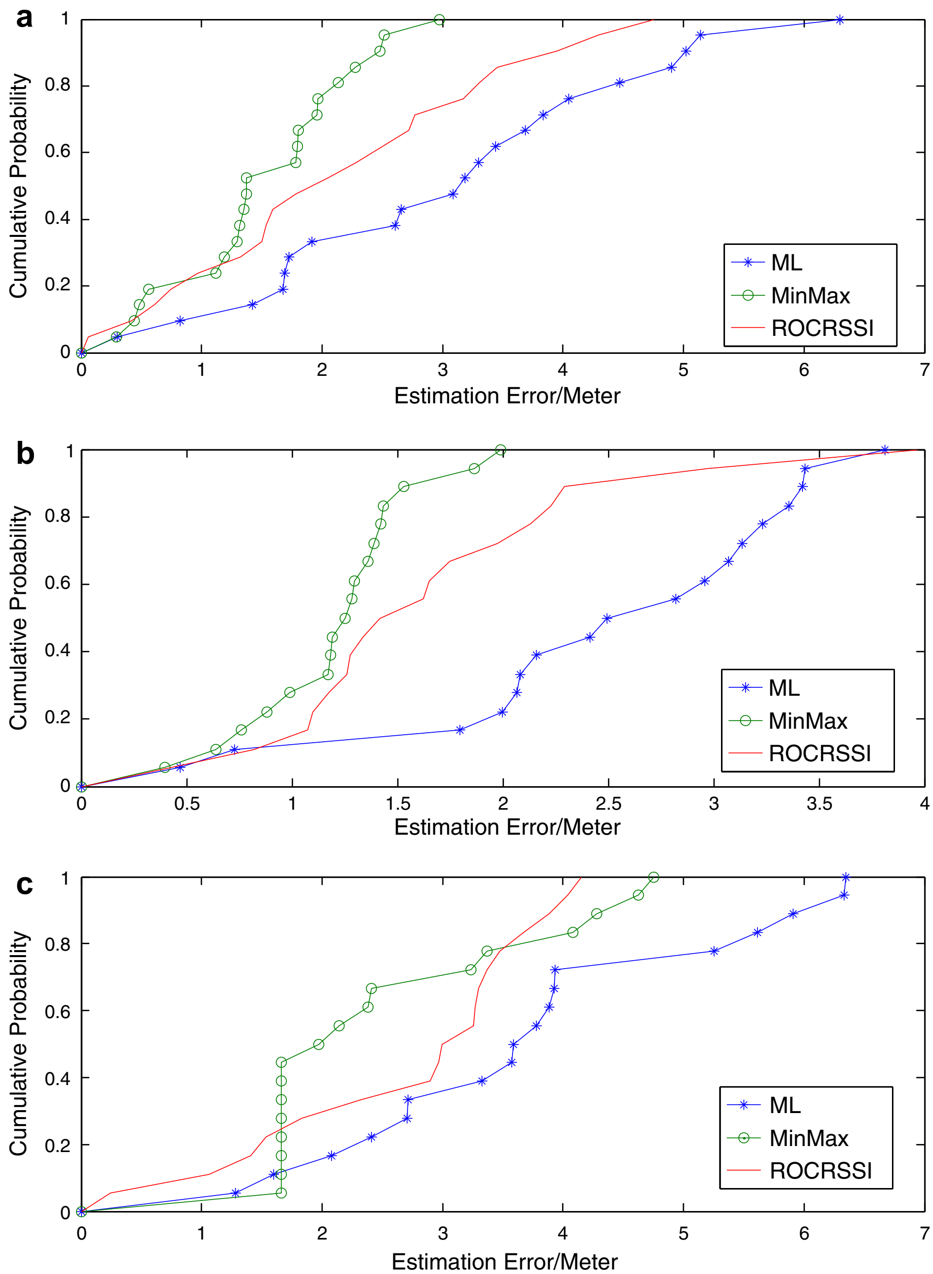

Fig. 6. CPF of: (a) test bed #1; (b) test bed #2; (c) test bed #3.

rithms (Maximum likelihood and MinMax) perform better in operating building than on construction jobsite, while ROCRSSI performs better on construction jobsite than in operating building (the errors converge). Further experimentation is necessary to investigate this inconsistent result.

3.2. RSSI map based analysis

Two sets of data collected in each test bed were prepared for kNN analysis. One data set was used as training data to create the RSSI map while the other data set was used as testing data to evaluate the algorithm's accuracy. The median RSSI value instead of average value was used at each sample point to generate the RSSI map. The authors conducted the analysis using various k values (k = 1, 2, 3, 4, 5, 6) while limiting the k value to not exceed the number of beacons in the test bed. Table 3 summarizes the accuracy of kNN algorithm with different k values in all three test beds. In both test beds, the accuracy increases as k value increases, although accuracy appears to level off quickly. This is consistent with prior literature [33,40,41]. The jobsite testbed has a better accuracy than operating building testbed does; this contradicts the findings for the other algorithms. MinMax performance is better than that of kNN in testbeds #1 and #2 across all k values. For testbed #3, kNN performs better than MinMax. This result might indicate that kNN could be preferred at a sparser beacon density; however, the results for testbed #1, which has a similar beacon density to testbed #3, are considerably worse. Some literature indicates that kNN is sensitive to absolute position of the beacons[40], and our findings may be confirming this.

4. Discussion

The research indicates that the MinMax algorithm has the best accuracy among the four localization algorithms tested on test

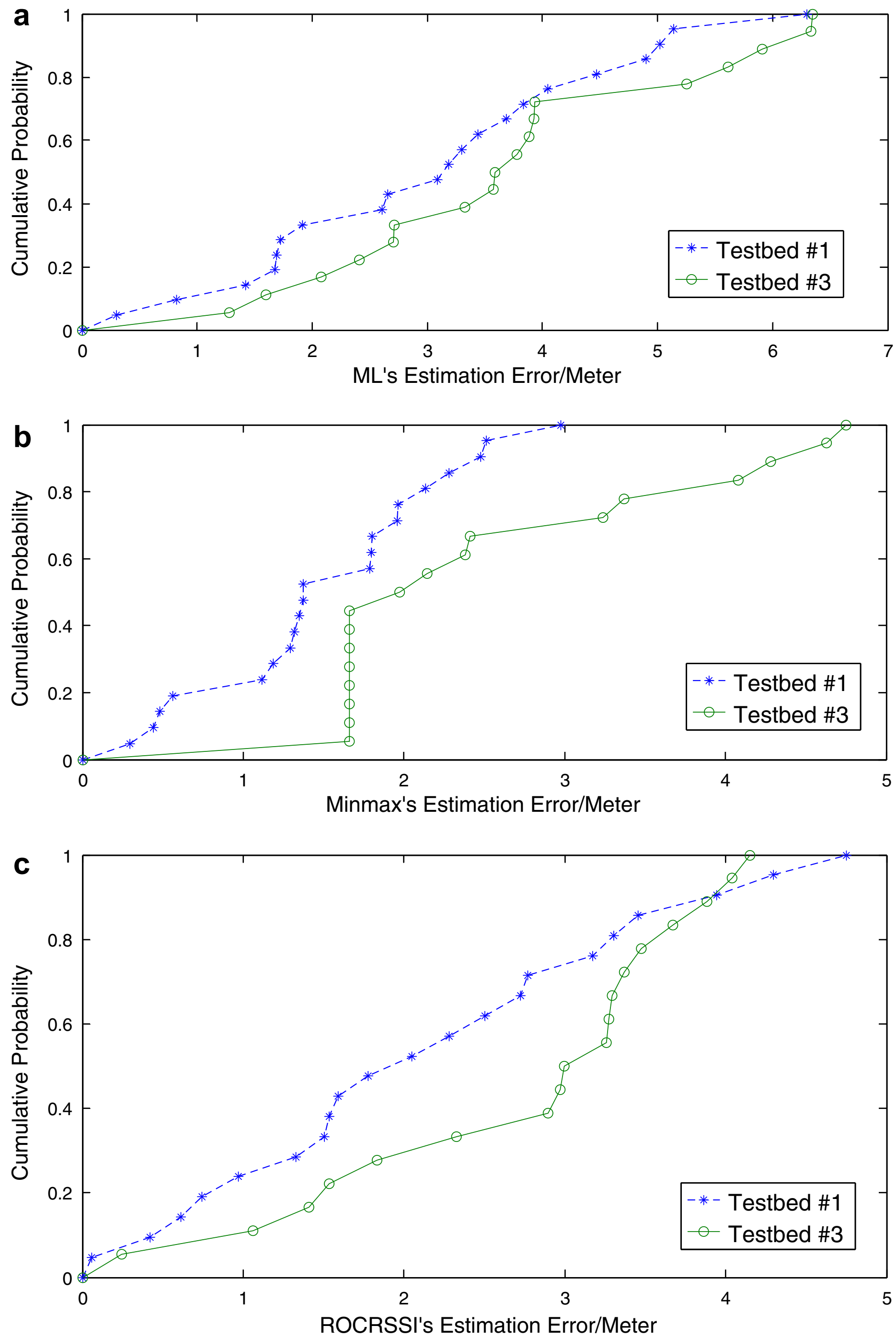

Fig. 7. Comparison of three algorithms' performance in test bed #1 and #3.

beds #1 and #2. *k*NN performs best in testbed #3, although it is better than MinMax by a median accuracy of only 0.5 m for its best result. The MinMax algorithm has other advantages over the other three algorithms: it is easier to implement and running time and data storage is linear with the number of beacons. This produces more possibilities to deploy the MinMax algorithm on resource constrained smart sensors and mobile networks (e.g., those with limited storage space, CPU speed and battery life), especially when there is a need to estimate the locations in a real time or near real time manner.

Although the ROCRSSI algorithm's performance is not as good as MinMax, it still has great potential for application on the construction jobsite since it does not require a predetermined path-loss model or map training as with *k*NN. Therefore, it can dynamically reflect the changes (e.g., workers moving and progress on the equipment installation) in the environment in real time without calibration. ROCRSSI performance is better than *k*NN for testbeds #1 and #2; as with MinMax, *k*NN performs better only in testbed #3.

Results for all four algorithms indicate that accuracy improves with beacon density. This is consistent with previous research [36]. What is less clear are the reasons behind the wide difference in accuracy between locations. For the MinMax, ROCRSSI, and ML algorithms, testbed #1 (operating building) has better performance

Table 3
*k*NN accuracy performance (error in meters) for different *k* values.

		k Value					
		1	2	3	4	5	6
#1 Operating Bldg	Average	2.93	2.69	2.6	2.61	NA	NA
	Median	3.05	2.46	2.37	2.54	NA	NA
	SD	1.52	1.14	1.09	0.98	NA	NA
#2 Jobsite (6 beacons)	Average	1.65	1.6	1.45	1.45	1.45	1.49
	Median	1.42	1.63	1.48	1.41	1.47	1.49
	SD	1.15	0.82	0.69	0.69	0.6	0.57
#3 Jobsite (3 beacons)	Average	2.07	1.72	1.7	NA	NA	NA
	Median	2.00	1.76	1.54	NA	NA	NA
	SD	1.25	0.84	0.78	NA	NA	NA

than testbed #3 (construction jobsite) for a similar beacon density. The opposite is true for *k*NN. There is evidence that the choice of beacon position may be affecting *k*NN [40], although this may be true for other algorithms as well. Certainly the construction jobsite has exposed ductwork, which may have caused some reflectivity-related issues. Further research is needed that specifically investigates the effects of reflectivity and interference with operating equipment and radios at jobsites to better understand the impact of these conditions.

From our results, it does appear that ML does not perform as well as the other algorithms and is not likely a candidate for further development in construction applications. Both MinMax and ROCRSSI appear to have very good results that compare favorably to *k*NN and have accuracy comparable to other techniques such as indoor GPS, which in one study was found to have an accuracy of 1.5–2.0 m [17]. All algorithms have a location accuracy that compares well to results obtained with RFID localization outdoors (with results of 3+ m [11]), suggesting that all RSSI algorithms may give adequate performance for materials management applications. Of course, for construction outdoors, simple RFID localization and GPS is generally much easier and cheaper to implement due to ease of line-of-sight readings. The advantages of RSSI algorithms are indoors where other techniques are constrained. It is unclear how much the accuracy would need to be increased in indoor applications – it is reasonable that greater accuracy would be required as spaces are generally tighter – but several algorithms have accuracy of 2 m or less. This is likely adequate for many materials management and safety applications.

Certain applications such as fall prevention may require greater accuracy than even the best results obtained above. It is possible to selectively increase beacon density in high risk areas. The tested beacon densities of 0.08–0.18 beacons/m^2 equate to 8–18 beacons per 100 m^2; a denser mesh is not difficult to set up in a limited area. Much of the setup time is calibration via learning or development of the path loss equation. If using an algorithm such as ROCRSSI that does not require prior calibration, the time to deploy a dense mesh is limited. This leads to an observation that the likely distribution of sensors on the jobsite will vary by area and need. Areas on jobsites where safety is a concern – such as near edges – could purposely have a denser distribution of devices. Other areas where safety concerns are less serious, or deployments where devices are attached to materials (such as pallets) that move, could have a much lower and likely irregular density of devices. Such areas may have lower precision requirements. In general, it is likely active jobsites will have an uneven beacon density across areas, and future research is needed to evaluate the reliability of localization algorithms in such conditions. More broadly, autonomous localization will need to be opportunistic to take advantage of a variety of data sources. This suggests the need for hybrid approaches to localization that mix input from a variety of sources such as RF and GPS and may also uses cues from the environment or data sources such as BIM models to determine location. At the same time, there will likely be an engineering design component to deployment of RF and related localization devices that considers desired accuracy for choice of deployment.

5. Conclusions

This research adds to the prior literature in construction by bringing evaluation to a live jobsite as well as evaluating path loss and range-free algorithms in addition to previously investigated *k*NN algorithms. Four algorithms were evaluated: MinMax, ML, ROCRSSI, and *k*NN. To evaluate the algorithms, over 50,000 readings were collected from two physical test beds: a live construction jobsite in downtown Austin, Texas and an operating building on the campus of the University of Texas. The live jobsite was used to create two testbeds of different beacon densities. Results show that both the MinMax and ROCRSSI algorithms have potential for future adoption, with results better than *k*NN in two testbed and nearly as good in the third testbed. Both MinMax and ROCRSSI have attractive properties that make them suitable for construction applications. MinMax is particularly suitable for real time applications as its resource needs are linear with the number of beacons. ROCRSSI is range-free and hence does not need prior calibration that is needed for path-loss and map-based algorithms. As such, ROCRSSI may be particularly useful for dynamic jobsites even though its accuracy is found to be somewhat worse than the MinMax algorithm.

Overall, the algorithms provide results that are comparable or better than accuracy obtained with outdoor localization using RFID tags, which is now in commercial application for construction jobsites. As such, the relatively low cost of radio frequency applications and strength in overcoming limitations of other techniques (principally, line-of-sight requirements) suggests that RSSI algorithms and equipment is likely well suited for indoor construction applications in materials management. Safety requirements may be more stringent and future research and development is needed, perhaps via mixed method and hybrid localization approaches. At the same time, results of this paper are limited to a single jobsite, and future research is needed to explore results on a range of jobsites.

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