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VBLM: High-Accuracy Localization Method with Verification Mechanism for Unstable-Signal Sensor Networks*

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Wireless sensor networks have received a lot of attention in recent years due to their wide spectrum of applications. Localization a technique used in ubiquitous sensor networks. Most localization techniques apply RSSI-based ranging techniques to compute the location of the object in a wireless sensor network. However, a wireless sensor network is a fading-signal environment that has noise, which causes RSSI to become unstable and leads to abrupt distance estimates. In this paper, we propose the Verification-Based Localization Method (VBLM) to alleviate the effect of unstable signals to provide high-accuracy location estimates in wireless sensor environments. VBLM filters noisy signals in the localization process. The sensor node uses a neighboring beacon to help verify the quality of received signal under acceptable communication cost. Noisy signals can thus be removed to decrease localization error. A set of experiments was conducted in an outdoor environment. The experimental results show that VBLM reduces the localization error in unstable signal sensor networks better than is possible with other localization methods.

Keywords: wireless sensor networks, unstable signal, localization, verification, RSSI, real-world sensor system simulation

1. INTRODUCTION

Recent advances in wireless sensor networks have led to increased development in wireless sensor applications. In real-world wireless sensor applications, *e.g.* smart-home applications, the localization component used to obtain the geographical locations of sensor nodes plays an important role in supporting location-based services [1-3]. For instance, a remote home-care system asks sensor nodes for the geographical locations of children to obtain their status. If the sensors detect a child near a warning area, *e.g.* stairs, the remote home-care system notifies the user.

Among proposed technologies [4], the RSSI-based localization technique (RSSI stands for *received signal strength indication*) is the most applicable to wireless sensors due to the low deployment cost. RSSI-based methods use a transmission antenna for localization, and thus do not require any additional expensive hardware.

Although the RSSI-based localization techniques are suitable for many wireless

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sensor applications, unstable radio signals make localization difficult [5, 6]. More specifically, when the antenna transmits network packets, the radio signal frequently becomes unstable [7]. The radio strength of packets becomes an outlier in the statistics data; the packets look like noise in the signal processing [8]. Using such packets in the localization process reduces accuracy. For example, the interference caused by furniture or moving people or pets leads to unstable radio signals in a smart-home environment. Therefore, the RSSI localization technique needs to consider these unstable signals when it is applied to smart-home environments.

Many small-area localization methods for sensor networks have been proposed [4, 5, 9, 10]. However, the proposed RSSI-based localization methods do not consider the effect of unstable signals on distance measurements. These methods directly use the collected signals for localization, which increases the localization error in real-world applications. In this paper, we propose the Verification-Based Localization Method (VBLM) to alleviate the effect of unstable signals to provide a high-accuracy location estimate in wireless sensor environments.

Assume that the unknown node is the node that requests localization, and that a beacon node is the node that knows its own position and translates a signal strength value (*i.e.*, RSSI) into distance. In traditional methods, the distance between the unknown node and a beacon node is estimated only through the cooperation between the two nodes themselves. Hence, it is difficult to determine whether a received signal is noise because the reliability of the received signal cannot be proved. In the proposed verification mechanism, the unknown node uses another neighboring beacon to help verify the quality of the received signal. This idea is based on a fact that the effect of environmental interference is regional, as shown in [11]. The region affected by the noise is called the *shadow zone* in the literature [11]. A sensor node that resides in the shadow zone causes the RF signal to substantial deviate from its mean. Based on the results in [11], verifying the quality of signals using nearby beacons is reasonable. To the best of our knowledge, no existing methods are based on the collaboration of beacons.

In VBLM, once the beacon node receives the request message from an unknown node, it broadcasts a ranging message so that the unknown node and another beacon node can simultaneously detect the message. Since the beacons have prior knowledge about their own locations, the beacon broadcasting the ranging message can verify the reliability of the broadcast signal by comparing the measured distance from another beacon. If the broadcast signal is reliable, the beacon broadcasting the ranging message calculates the distance between the unknown node and the beacon, and then returns the measured distance to the unknown node. Otherwise, the beacon informs the unknown node to retry the ranging process. Using this verification mechanism, VBLM can filter most unstable signals; it delivers the reliable signals to the location calculation component. Although the verification mechanism produces more communication between nodes, the communication cost for VBLM is acceptable. A set of real-world experiments was conducted in an outdoor environment to show the performance of the proposed method. A reduction of the error of distance estimates and location estimates shows that VBLM is reliable in unstable-signal sensor networks. The results show that the accuracy provided by VBLM is higher than those of other localization methods.

The rest of this paper is organized as follows. Section 2 describes related work on localization technologies. The system environment is described in section 3. The proposed localization algorithm is proposed in section 4. Sections 5 and 6 contain the experiment results and conclusion, respectively.

2. RELATED WORK

This section describes current localization techniques in wireless sensor networks. The localization methods can be divided into two classes: range-based schemes and range-free schemes. The classification of localization methods is shown in Fig. 1. The range-based schemes focus on sensor nodes that have the ability to measure the distance or angle for 1-hop neighboring nodes. Range-based schemes include RSSI [5, 9, 10], TOA [12, 13], and TDOA [14, 15]. Range-free schemes focus on sensor nodes that infer the distance between nodes using the transmission information in the sensor network, such as hop-count messages [16]. The most popular range-free scheme is DV-Hop [16].

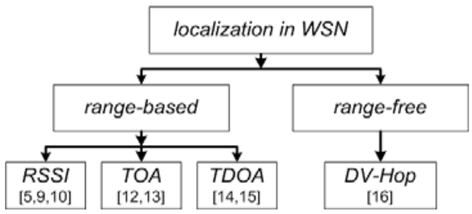


Fig. 1. Classification of localization techniques in wireless sensor networks.

RSSI-based localization techniques [5, 9, 10] read the RF signal from a received packet, and use the information to estimate locations. The RF signal attenuates with increasing broadcast distance. Thus, sensors can read the RSSI from the RF signal sent by other sensor nodes, and estimate the distance to the transceiver node. RSSI-based techniques do not require any special hardware for ranging; the cost and energy consumption are thus low. However, the RF signal is easily interfered with by the noise in the wireless environment, making the corresponding RSSI values unstable. Consequently, sensors could generate a large error from RSSI values. Some methods [7] proposed for cleaning sensor readings are based on temporal statistics; however, localization techniques need the signals to be received at the same timestamp. In this paper, we focus on the properties of localization techniques, and propose an efficient localization method that considers noisy signals.

Time of arrival (TOA) techniques [12, 13] used the time that it takes for a packet to travel from the transceiver to the receiver to estimate distance. TOA techniques require sensors to be well synchronized in order to obtain accurate distance estimates. However, due to energy consumption, computational power, and environment limitations, the synchronization of all sensors is extremely difficult in wireless sensor networks. Time difference of arrival (TDOA) based techniques [14, 15] remove some of the inconveniences of TOA. TDOA simultaneously sends a radio signal and an ultrasound pulse to the receiver. Based on the difference between the traveling speed of the two types of message, the receiver can estimate the distance by observing the time difference of the message arrival.

Range-free DV-Hop [16] estimates distance based on inference, instead of measuring it directly. DV-Hop evaluates the distance between two nodes by multiplying the number of hops by the average distance of a hop. Thus, the distance of two nodes is inferred from the geometric relationships in the topology of the sensor network. Although DV-Hop does not require special hardware for ranging, the distance estimate is less accurate compared to range-based techniques. The ranging error can be quite large when the sensor nodes are not uniformly distributed in the sensor network.

3. ENVIRONMENT

The wireless sensor network comprises sensors nodes. These nodes are either beacon nodes or unknown nodes, as shown in Fig. 2. Beacon nodes know their own absolute location in the sensor network. Since the absolute locations of the beacons are known, the absolute distance can be deduced by processing pre-measured positions (*Euclidean*(B_1, B_2) in the figure). Unknown nodes need to request their current locations (*U* in the figure). In many smart-home application scenarios, the unknown nodes represent the moving objects in the sensor network [17].

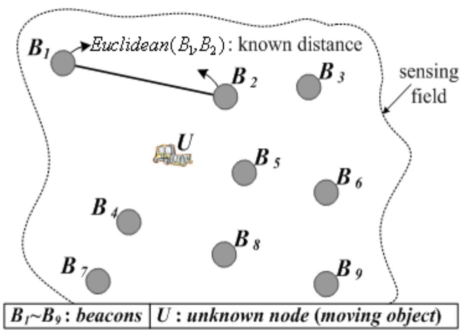


Fig. 2. Illustration of wireless sensor environment.

In general, a sensor node has four major components: the sensing unit, the processing unit, the communication unit, and the power unit [18]. The present paper focuses on the communication unit and the processing unit in the localization process. The communication unit is equipped with an antenna and is used to send or receive RF messages. The communication component also has an analog-to-digital converter (ADC) to recognize the RSSI of a received message. Common chipsets for the up-to-date sensors include ChipCon CC1000 and ChipCon CC2420 [19]. The communication component can operate on over 30 transmission power levels and multiple transmission frequencies. The settings of the communication component affect the transmission range and quality.

The processing unit comprises a processor and a memory unit so that a sensor node can run certain designated tasks, such as noise verification and location calculation. The training data for the RSSI to distance calculations are stored in the memory of the wireless sensor. When the RSSI of a message is received, the processor can match the RSSI to all possible distances.

4. VERIFICATION-BASED LOCALIZATION METHOD (VBLM)

In this section, we present the Verification-Based Localization Method (VBLM), which adopts a threshold-based error control approach to determine erratic RSSI values. The basic idea of VBLM is that the sensor node uses another neighboring beacon to help verify the quality of the received signal. Noisy signals can thus be removed to avoid increasing the error in localization. Fig. 3 shows the idea behind VBLM. Assume that B_1 and B_2 are the beacon nodes and U is the unknown node. In this case, we also assume that B_1 is selected as the ranging node. Initially, B_1 broadcasts the ranging-request message to the neighbor beacon node B_2 and the unknown node U, and collects the RSSI values that U and B_2 read from the ranging request message (say, – 62dBm and – 60dBm in this example, respectively). Next, the distance between B_1 and B_2, *Estimate*(B_1, B_2), is evaluated by comparing the RSSI values to the entries in the signal-matching table, obtaining 100cm (RSSI(– 62dBm) = 100cm). Since the estimated distance *Estimate*(B_1, B_2) equals the reference distance between B_1 and B_2, *Euclidean*(B_1, B_2), that is computed from the pre-trained beacon positions, we treat the signal of the ranging-request message as reliable. Notice that the distance error is set to 0cm in this example for simplicity. Since the signal is reliable, B_1 continues to evaluate distance *Estimate*(B_1, U) by looking up the signal-matching table, obtaining 80cm (RSSI(– 62dBm) = 100cm). Finally, B_1 reports *Estimate*(B_1, U) = 80cm to U.

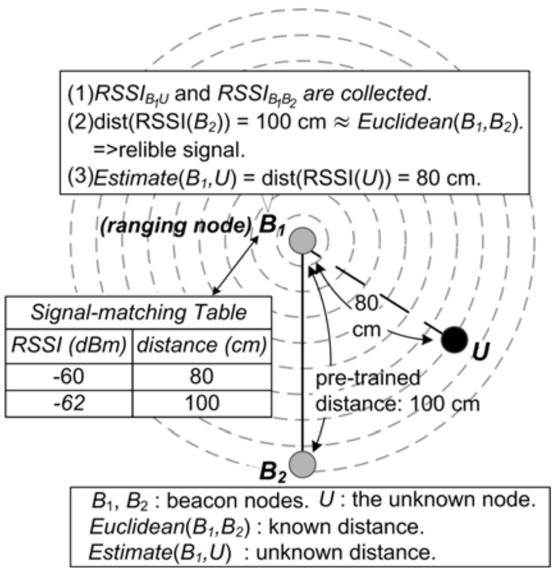


Fig. 3. Illustration of the basic idea of VBLM.

The flow diagram of VBLM consists of three stages, as shown in Fig. 4. In the first stage, the signal matching model is used to build a signal-matching table, as shown on the left side of the figure, for each beacon. A beacon equipped with the signal-matching table can translate RSSI values into distance estimates. The second stage is the Verification-Based Ranging Algorithm (VBRA), which handles the ranging task. VBRA is the most

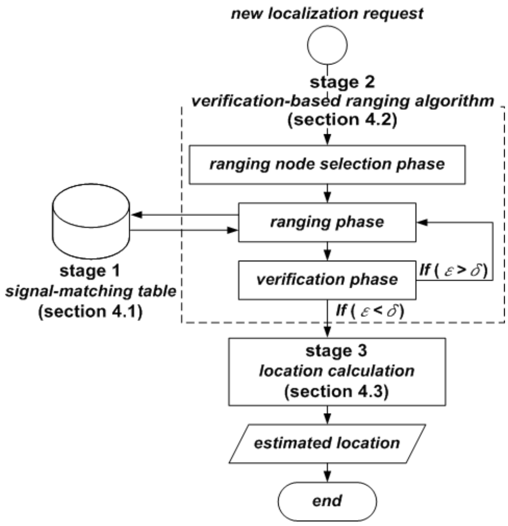


Fig. 4. VBLM flow diagram.

critical component in our proposed method. The main objective of VBRA is to verify whether the distance estimates are reliable. If the verification result is reliable (that is, $\varepsilon < \delta$ in the figure, where ε is the distance error and δ is the pre-defined error threshold), then the ranging result is sent back to the unknown node. Otherwise (that is, $\varepsilon > \delta$), the ranging result is discarded and VBRA is re-executed. After obtaining the verified ranging results, the third stage, location calculation, is used to estimate the location from the verified distance estimates. When nodes receive a distance from at least three beacons, the location can be estimated. The details of the three stages are presented in the following three subsections.

4.1 Signal-Matching Table

The signal-matching table is designed to match possible distances for a given RSSI. The table records the mapping between RSSI and the distance. We adopt the signal-matching model to design the signal-matching table because the proposed RF attenuation model [20] cannot adequately represent the multi-path effect in real-world applications. In this work, the signal-matching table is called the *signal-to-distance table*, which is used to keep track of the distance units that correspond to each RSSI value. After constructing the signal-to-distance table, a beacon node can find the most probable distance estimate by running the ranging algorithm discussed in section 4.2.

In order to build the signal-to-distance table, RSSI values at various distances need to be collected and organized. The flow diagram of building the signal-to-distance table is illustrated in Fig. 5. The settings for the RSSI training process are initialized, including the training distance interval, length of distance, number of RSSI samples, and transmission power. After the settings are initialized, the RSSI training process starts to collect RSSI values at each distance interval. Then, the signal-to-distance table is built by organizing the fixed interval of RSSI values and the distance range from received messages in the RSSI training process.

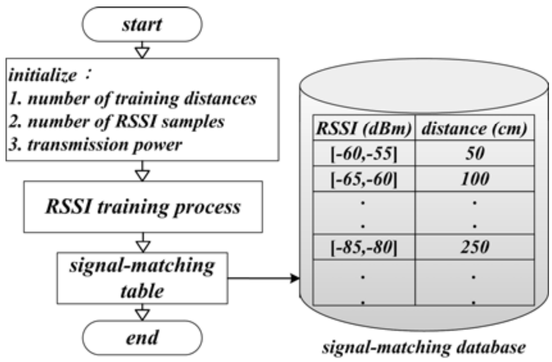


Fig. 5. Flow diagram of building the signal-to-distance table.

Notice that the signal-to-distance table only shows a one-to-one mapping. In real-world cases, RSSI and distances in the table can have a one-to-many mapping. In this paper, we focus on filtering noisy signals to avoid using them in the location estimation. To achieve this goal, the proposed method needs to translate a received signal to a distance by looking up the signal-distance matching table, so that the proposed method can next identify noises in the distributed sensor network. Therefore, the signal-distance matching table is an auxiliary tool used in the proposed method. Interested readers may refer to related studies, such as [21], for more details about the signal-distance matching issue.

4.2 Verification-Based Ranging Algorithm (VBRA)

Fig. 6 shows the Verification-based Ranging Algorithm (VBRA). The algorithm includes three phases: (1) ranging node selection phase, (2) ranging phase, and (3) verification phase.

4.2.1 Phase 1: ranging node selection phase

In order to obtain a distance between the unknown node and a beacon, the unknown node selects a beacon node out of the neighboring beacon nodes that are one-hop distance from the unknown node. The condition of the selected ranging node is that the ranging node should have the greatest RSSI value because in many practical situations [5], the greatest RSSI value has the lowest probability of having noise.

The steps of this phase are shown as steps 1-3 in 0. In this phase, the unknown node broadcasts a ranging request message to the nearby beacon nodes. Next, the neighboring beacon nodes return their RSSI back to the unknown node. Then, the unknown node selects the beacon node with the largest RSSI to be the ranging node.

4.2.2 Phase 2: ranging phase

The ranging phase measures distances from the ranging node to the unknown node and other beacon nodes. The steps are shown as steps 4-6 in Fig. 6. The ranging node starts by broadcasting a ranging message to 1-hop neighboring nodes. Notice that the

Verification-based Ranging Algorithm

Input:
U: denotes the sensor node U that issues the ranging request; // *i.e.*, unknown node.
δ: denotes the ranging result error threshold;

Output: $dist_m(B_n, U)$; // $dist_m(B_n, U)$ is the measured distance from B_n to U.

// **Phase 1: Ranging-node selection phase**
Step 1: U broadcasts a *ranging request message* to 1-hop neighbors;
Step 2: All neighbors detect RSSI from *ranging request message*, and return RSSI to U;
Step 3: U selects the nearest beacon B_n with the largest RSSI;

// **Phase 2: Ranging phase**
// B_m is the closest beacon from B_n.
// $dist_m(B_n, B_m)$ is the measured distance from B_n to B_m.

Step 4: B_n broadcasts a *ranging message* to 1-hop neighboring nodes;
Step 5: After U and B_m detect $RSSI_U$ and $RSSI_{Bm}$ from *ranging message*, respectively, U and B_m return $RSSI_U$ and $RSSI_{Bm}$ to B_n;
Step 6: B_n converts $RSSI_{Bm}$ to $dist_m(B_n, B_m)$;

// **Phase 3: Verification phase**
// $dist(B_n, B_m)$ is the actual distance between B_n and B_m.
// δ is pre-defined error threshold.

Step 7: B_n computes $dist(B_n, B_m)$;
Step 8: $\varepsilon = |dist_m(B_n, B_m) - dist(B_n, B_m)|$;
Step 9: if ($\varepsilon > \delta$) then
    goto step 1;
  else
    B_n converts $RSSI_S$ to $dist_m(B_n, U)$;
    return $dist_m(B_n, U)$;
  end if

Fig. 6. Verification-Based Ranging Algorithm (VBRA).

neighboring nodes have to include the unknown node and beacon nodes. After receiving the ranging message, neighboring nodes returns the RSSI value of the received message to the ranging node. Subsequently, the ranging node converts the RSSI to distance estimates by looking up the signal-to-distance table.

4.2.3 Phase 3: verification phase

The verification phase determines whether the distance estimates generated in the ranging phase are reliable. The condition is the quality of the distance error from the ranging node to the beacon node. If the distance error between the absolute distance and the estimated distance is less than the pre-defined error threshold, the ranging result from the ranging node to the unknown node is reliable and can be used for the location calculation in the next stage.

This phase is shown as steps 7-9 in Fig. 6. In this phase, the ranging node starts by computing the absolute distance between beacons based on the pre-trained positions of beacons. The ranging node then computes the distance error ε between the absolute and estimated distances for the beacon node. If the error ε is less than the error threshold δ, the ranging node sends the distance estimate to the unknown node. Otherwise, VBRA discards the current distance estimate and goes to step 1 to re-execute the algorithm to obtain a new ranging result. The process is stopped when the condition $\varepsilon < \delta$ is met.

The parameter error threshold δ in the algorithm is pre-determined by the system administrator according to the actual environment. If the error threshold δ is too large, the verification mechanism cannot filter abrupt signals. In this case, VBRA degrades to the traditional ranging methods. On the other hand, if the error threshold δ is too small, VBRA frequently aborts the ranging result. In this case, the sensor network wastes a lot of additional computation and communication. Hence, setting the proper value of the error threshold δ is important for VBRA. Since the error threshold δ is sensitive to the physical environment, it is difficult to derive a general rule for setting it. Some practical studies [5] might help the system administrator increase his or her familiarity with the deployed environment.

The packet size used in VBRA communication is small. Fig. 7 shows the packet format for the unknown node and beacons. The packet consists of four attributes: Destination, RSSI, Source, and Location. The size of the packet is 11 bytes, which is much smaller than the default packet size (40 bytes) in the TinyOS system [22]. The Destination attribute records the ID of the ranging node. The RSSI attribute contains the RSSI value of the received ranging message. The last two attributes, Source and the Location, represent the node ID and the location of the message source, respectively. Notice that a null location is used for unknown nodes.

RSSI message from U			
destination	RSSI	source	location
B_1	$RSSI_U$	U	null

RSSI message from B_2			
destination	RSSI	source	location
B_1	$RSSI_{B2}$	B_2	(X_2, Y_2)

Fig. 7. Message format in VBRA.

4.3 Location Calculation

Since the distance measurements could be inexact, the location of the unknown node is uncertain and bounded in a region [9], as shown by the gray region in Fig. 8. In the location calculation, the classic multilateration algorithm is employed to estimate the location. When the unknown node receives the distances from nearby beacons, the unknown node can estimate its location as follows.

Assume that the locations of n beacons are $A_i(x_i, y_i)$, $i = 1, 2, 3\ldots, n$ and that the location of the unknown node U is (x_u, y_u). Also assume that VBLM ranging distances are d_i, $i = 1, 2, 3\ldots, n$. The distance estimation between U and other beacons can be represented by a set of equations:

$$\begin{cases} (x_u - x_1)^2 + (y_u - y_1)^2 = d_1^2 \\ (x_u - x_2)^2 + (y_u - y_2)^2 = d_2^2 \\ \vdots \\ (x_u - x_n)^2 + (y_u - y_n)^2 = d_n^2 \end{cases} . \tag{1}$$

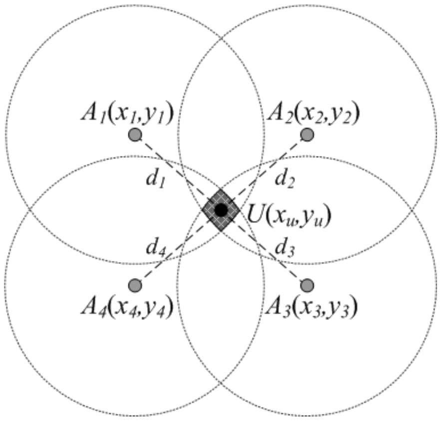


Fig. 8. Illustration of the possible region of location calculation.

In order to obtain the location of node U, the above equations are transformed into matrix form as follows.

$$2 \cdot \begin{bmatrix} x_n - x_1 & y_n - y_1 \\ x_n - x_2 & y_n - y_2 \\ \vdots & \vdots \\ x_n - x_{n\text{-}1} & y_n - y_{n\text{-}1} \end{bmatrix} \cdot \begin{bmatrix} x_u \\ y_u \end{bmatrix} = \begin{bmatrix} (d_1^2 - d_n^2) - (x_1^2 - x_n^2) - (y_1^2 - y_n^2) \\ (d_2^2 - d_n^2) - (x_2^2 - x_n^2) - (y_2^2 - y_n^2) \\ \vdots \\ (d_{n-1}^2 - d_n^2) - (x_{n-1}^2 - x_n^2) - (y_{n-1}^2 - y_n^2) \end{bmatrix} \tag{2}$$

Notice that Eq. (2) is an over-determined system of the linear equations; hence, the location of U can be obtained by employing the Minimum Mean Square Error (MMSE) method, and can be represented as $U = (A^T A)^{-1} A^T b$, where

$$A = 2 \cdot \begin{bmatrix} (x_n - x_1) & (y_n - y_1) \\ (x_n - x_2) & (y_n - y_2) \\ \vdots & \vdots \\ (x_n - x_{n\text{-}1}) & (y_n - y_{n\text{-}1}) \end{bmatrix}, b = \begin{bmatrix} (d_1^2 - d_n^2) - (x_1^2 \text{-} x_n^2) - (y_1^2 - y_n^2) \\ (d_2^2 - d_n^2) - (x_2^2 \text{-} x_n^2) - (y_2^2 - y_n^2) \\ \vdots \\ (d_{n\text{-}1}^2 - d_n^2) - (x_{n\text{-}1}^2 \text{-} x_n^2) - (y_{n\text{-}1}^2 - y_n^2) \end{bmatrix} \text{ and } U = \begin{bmatrix} x_u \\ y_u \end{bmatrix}.$$

We use a simple example to demonstrate the above equations for the location calculation. Assume that $A_1(x_1, y_1) = (0, 7)$, $A_2(x_2, y_2) = (8, 7)$, $A_3(x_3, y_3) = (8, 0)$, and $A_4(x_4, y_4) = (0, 0)$ in Fig. 8, and that the distances between the unknown node U and the beacons are $d1 = d2 = d3 = d4 = 6$. Then, Eq. (2) can be rewritten as:

$$\begin{bmatrix} 0 & -14 \\ -16 & -14 \\ -16 & 0 \end{bmatrix} \cdot \begin{bmatrix} x_u \\ y_u \end{bmatrix} = \begin{bmatrix} -49 \\ -113 \\ -64 \end{bmatrix}. \tag{3}$$

After algebraic operations on Eq. (3), the location of the unknown node (x_u, y_u) is obtained as (4, 3.5).

4.4 Interaction Analysis among Nodes

Fig. 9 shows the sequence diagram of VBLM. The sequence diagram shows the interaction among the nodes, the integration viewpoint of VBRA (the ranging-node selection phase, ranging phase, verification phase), and the location calculation module. Assume that the two beacons used for localization of the unknown node U are B_1 and B_2, and that beacon B_1 is the nearest beacon to the unknown node U (that is, B_1 is the ranging node). The settings are consistent with those in Fig. 3. In the figure, steps 1-9 demonstrate the interactions in the VBRA algorithm and steps 10-11 show the location calculation module. From the sequence diagram, the unknown node U and the ranging node B_1 only send three communication messages, respectively. Hence, the communication overhead of VBLM is limited and acceptable.

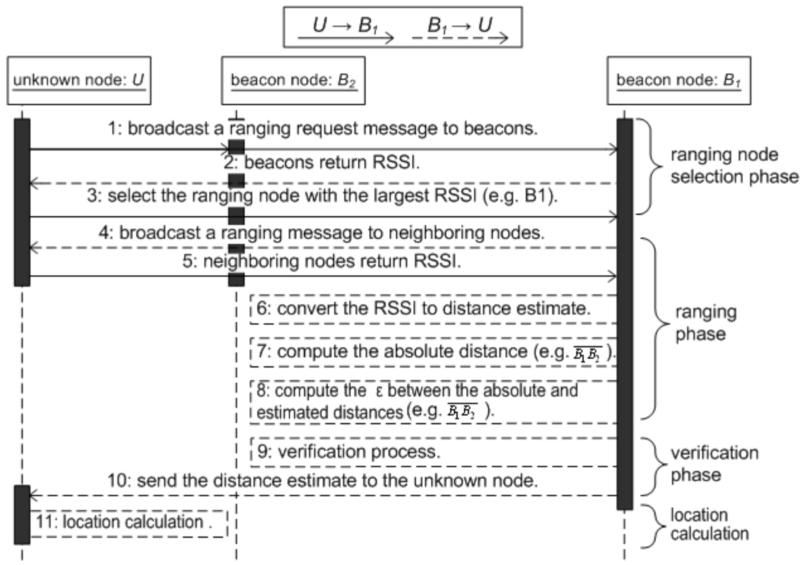


Fig. 9. Sequence diagram of VBLM.

4.5 Discussion

VBLM has four advantages, (1) The proposed technique offers distance estimate verification, (2) VBLM can be easily implemented, (3) users can set the error threshold according to the application needs of their environment, and (4) VBLM provides reliable distance estimates. In the experiments, we found that VBLM can filter the environmental noise that affects the quality of RSSI. Therefore, VBLM can generate reliable distance estimates.

VBLM can also be adopted in various RF signal-based ranging techniques, which includes TOA, TDOA, and RSSI. In this paper, we implement VBLM using RSSI because the hardware is cheap and widely used in many sensor applications. The proposed method is basically quite extensive, and can be accommodate to other ranging techniques through slight modification. Due to the page length limitation, we leave the issue as future work.

5. EXPERIMENT RESULTS

This section contains a detailed quantitative analysis that verifies the proposed method, and a performance comparison with pure RSSI localization schemes, including the multilateration algorithm and the trilateration algorithm [23]. The system prototype implemented for the experiment study was designed using the sensor programming language nesC [24] on Tmote Sky motes [25]. The prototype is an extension from our previous work [9, 26]. We ran the experiments in an outdoor environment of Southern Taiwan University to obtain real-world results.

Parameter	Settings
Number of beacons	4 (simple grid topology)
Distance between two neighboring beacons	100cm, 300cm, and 500cm, respectively.
Node density	100×100 (cm^2): 4 (nodes/m^2) 300×300 (cm^2): 0.4444 (node/m^2) 500×500 (cm^2): 0.16 (node/m^2)
Localization samples	50 samples for each experiment
Interval of two samples	1 second
Error threshold	50cm

Fig. 10. Default settings of each parameter in the simulation.

The experimental settings are shown in Fig. 10. We deployed four beacons in a grid topology. The four-beacon deployment is almost the minimum scale for a sensor localization system; thus, our experiment performance can be treated as the benchmark under a poor-resource scenario. In order to observe the performance under various settings of the node density, the distance of two neighboring beacons was set to 100cm, 300cm, and 500 cm, respectively [27]. Our experimental settings can be applied to many real applications. For example, the setting $500 \times 500\text{cm}^2$ almost covers a room, which should be large enough for many smart-home applications. In addition, the experimental results can be easily scaled to larger areas. For example, 0 shows the relationship between a $10 \times 10\text{m}^2$ deployment and a $5 \times 5\text{m}^2$ deployment. In this work, the experimental results are for an area of $5 \times 5\text{m}^2$ (say, area A in the figure). Because the size of areas B, C, and D is also $5 \times 5\text{m}^2$, the localization results in the three areas should be similar to the results in area A. For each experimental setting, 50 experimental samples were collected for statistical significance. The interval between two continuous experimental samples was set to one second. After all experimental data were collected, we plotted the results in cumulative probability (CDF) graphs to show the positional precision and accuracy.

In the experiments, we placed a carton near the unknown node to emulate the interference of noise which affects both the unknown node and neighboring beacons. The error threshold of our scheme was set to 50cm.

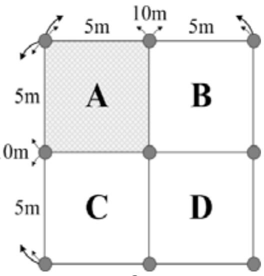
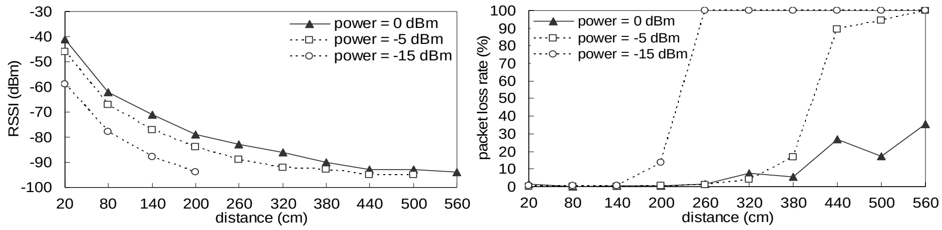


Fig. 11. Relationship between a $10 \times 10\text{m}^2$ deployment and a $5 \times 5\text{m}^2$ deployment.



(a) RSSI. (b) Packet loss rate.

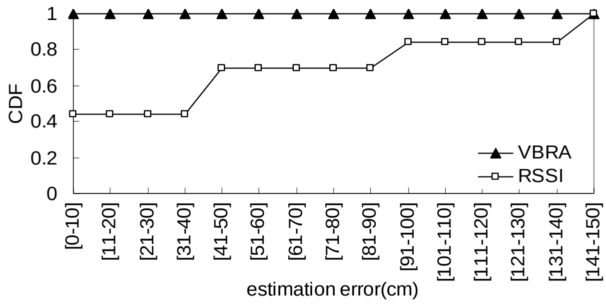
Fig. 12. RSSI values and packet lost rate for various transmission power levels at various distance settings.

5.1 Characterizing RSSI versus Distance

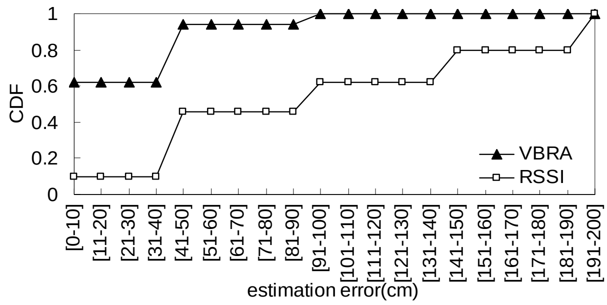
In the first experiment, we show the RSSI property of our hardware and determine a proper value of the transmission power for broadcast messages. The results are shown in Fig. 12. Fig. 12 (a) shows the RSSI values for various transmission power levels at various distance settings (refer to the RSSI training process in Fig. 5). In the figure, the curves of the transmission power indicate that the capacity of the transmission distance is from 200cm to 560cm; the curve of 0dBm can transmit messages with the longest distance. Fig. 12 (b) shows the packet loss rate in the experiments. From the figure, most power levels have a high packet loss rate when the distance of two neighboring beacons is over four meters. Hence, we suggest setting the measurable distance of two neighboring nodes to less than six meters. Otherwise, the localization scheme could have poor performance due to the hardware limitation. In the rest of the experiments, we set the transmission power to 0dBm, the maximum ranging distance to 500cm, and the maximum localization area to $500 \times 500\text{cm}^2$.

5.2 Effect of Noise on Distance Estimations

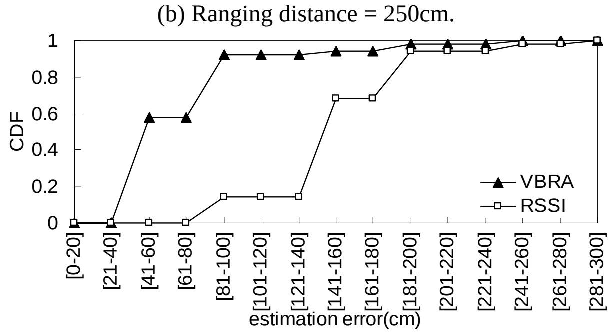
In order to evaluate the validity of VBRA with environmental interference, we conducted an experiment for comparing the distance estimations between VBRA and the traditional RSSI ranging algorithm [10]. Fig. 13 shows the comparison between VBRA and the traditional RSSI ranging algorithm for various distances (*i.e.*, from 100cm to 500cm) in a noisy environment. The RSSI shows that the environment is affected by noise; the RSSI ranging algorithm obtains low-accuracy ranging results in most cases (*i.e.*, low cumulative probability CDF). These results show that VBRA can remove noisy signals. The estimation error of VBRA in all experimental samples was less than 40 cm for ranging distances of less than 250cm (Figs. 13 (a) and (b)). This shows that the noisy signals that cause ranging error of over 50 cm were removed. From the results, we can see that VBRA is more accommodative than the RSSI ranging algorithm in the noisy environment.



(a) Ranging distance = 100cm.



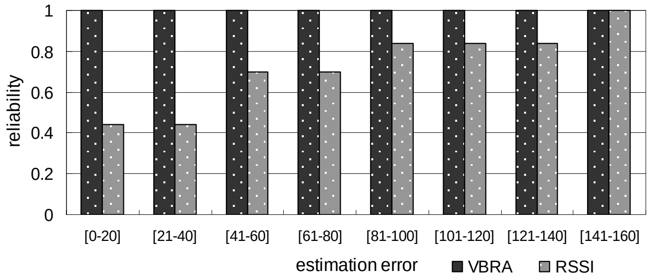
(b) Ranging distance = 250cm.



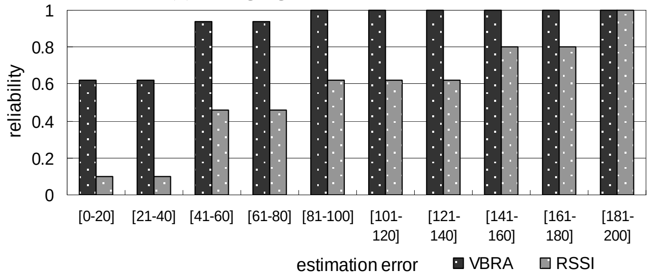
(c) Ranging distance = 500cm.

Fig. 13. Ranging result comparisons between VBRA and the traditional RSSI ranging algorithm for various distances.

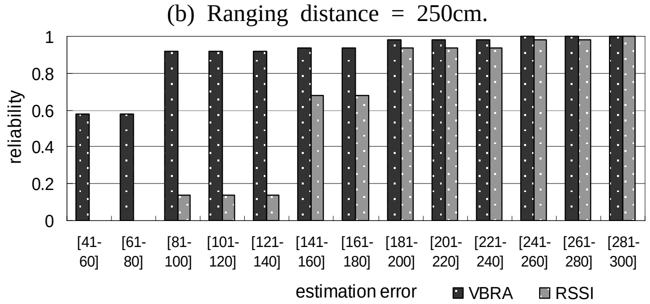
Fig. 14 shows of reliability of ranging observations for the two ranging algorithms at various ranging distances. The reliability is defined as the number of signals that satisfy the estimation error limit to total number of signals. From the results, the RSSI ranging algorithm produced low reliability, indicating that noise existed in the experi-



(a) Ranging distance = 100cm.



(b) Ranging distance = 250cm.



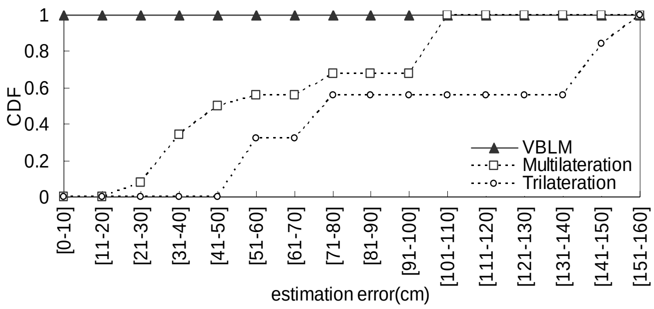
(c) Ranging distance = 500cm.

Fig. 14. Ranging reliability comparisons between VBRA and the traditional RSSI ranging algorithm for various distances.

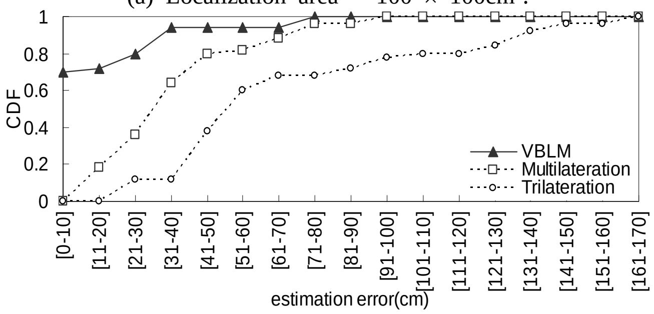
mental environment. VBRA greatly improved the reliability. For the short ranging distances in our experiment, VBRA removed all noise. For small estimation error at long ranging distances (*e.g.*, ranging distance = 250cm and 500cm), VBRA removed 60 percent of noise. The reliability of the RSSI ranging algorithm was less than 0.2; that is, less than 20 percent of signals were usable in the localization. Therefore, the verification mechanism efficiently removed noise at various ranging distances, ensuring the quality of collected signals.

5.3 Effect of Noise on Localization

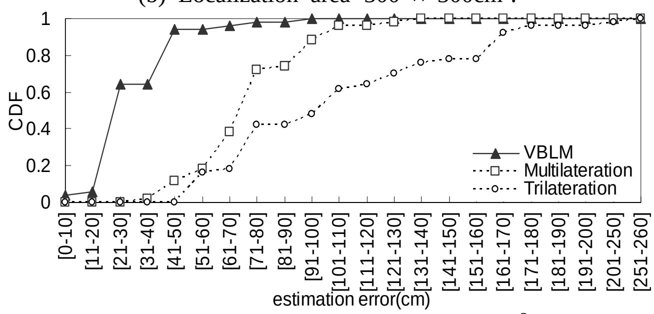
In order to evaluate the accuracy of VBLM with environmental interference, we designed an experiment for comparing the estimation error between VBLM and two related algorithms, the multilateration algorithm and the trilateration algorithm [23]. The results are shown in Fig. 15. Recall that the error threshold was set to 50cm in the experiments.



(a) Localization area = 100 × 100cm^2.



(b) Localization area=300 × 300cm^2.



(c) Localization area = 500 × 500 cm^2.

Fig. 15. Comparisons of localization error for various area sizes.

The result shows that VBLM obtains CDF = 1.0, which means the estimation error of all experimental samples was less than 50cm. In most cases, the estimation error was even less than 30cm. VBLM produced a much higher accuracy than those of the other two algorithms. The reason for the superior performance is as follows. Most current localization methods can generate high-accuracy locations if they obtain high-quality ranging results. However, a big problem in wireless sensor networks is that the receiving signals are easily interfered with due to the antenna's physical properties (*e.g.*, low power rate for short-range communication). Thus, the ranging results from the interfered with signals may lead the location calculation process to generate locations with a large error. The proposed scheme can filter the low-quality signals (interfered with by noise) and keep the high-quality signals for the location calculation process. Using the efficient removal technique for noisy signals, the proposed method can obtain high-accuracy locations. In contrast, the multilateration algorithm and the trilateration algorithm do not deal with noisy signals, so their results have a large estimation error.

5.4 Effect of the Number of Beacons

In this experiment, we studied the effect of the number of beacons for various localization methods. The results are shown in Fig. 16. In an ideal environment, a location the mulateration algorithm with four beacons does not always perform better than that with three beacons. Since some of the ranging results are affected by noise, a localization scheme could generate locations with a large estimation error even if the scheme has more ranging results for the location calculation. Therefore, removing noisy signals is a critical step in a localization scheme. Compared to the multilateration algorithm, VBLM is designed to aggressively filter noisy signals in the ranging stage (*i.e.*, using VBRA) to obtain high-accuracy locations.

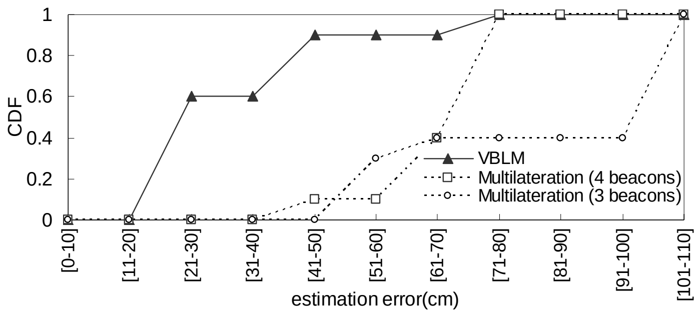


Fig. 16. Estimation error for various numbers of the beacons.

6. CONCLUSION AND FUTURE WORK

Localization is a critical technique in wireless sensor applications. However, previous RSSI-based localization methods do not consider the effect of unstable RF signals, which negatively affects positioning accuracy. In this paper, we proposed the verification-based localization method, VBLM, which improves the positioning accuracy in unstable-signal wireless sensor environments. VBLM can verify the reliability of distance estimates during the ranging process, allowing the system to generate more reliable ranging results. Furthermore, users can set the degree of accuracy by adjusting the error threshold.

The proposed verification mechanism is highly extendable. There are three possible extensions for this work. The first is to study more detailed factors, such as the failure ratio of localization, or the relationship between the error threshold and the estimation error. The second direction is to study the positioning error under various levels of environmental noise for the sensor localization area. In this paper, VBLM directly removed unreliable signals. However, in an environment that causes a low level of noise, a noisy signal could be still usable after some adjustment. We can design a new algorithm that gives a confidence value to a signal. We can also study the relationship between the position error and the level of noise. The third direction is to extend the proposed verification mechanism to other localization systems. If the proposed verification mechanism can be applied to other kinds of localization system, it is important to provide more experimental results, such as the verification mechanism with fingerprinting algorithms or the verification mechanism with angle-of-arrival algorithms.

REFERENCES

1. Y. Rahal, P. Mabilleau, and H. Pigot, "Bayesian filtering and anonymous sensors for localization in a smart home," in *Proceedings of the 21st IEEE International Conference on Advanced Information Networking and Applications Workshops*, Vol. 2, 2007, pp. 793-797.
2. Y. Rahal, P. Mabilleau, and H. Pigot, "Anonymous localization in a smart home," in *Proceedings of the 2nd International Conference on Technology and Aging*, 2007, pp. 793-797.
3. Y. Xu, J. Ford, F. S. Makedon, D. O. Popa, H. Huang, and L. Shen, "In-home localization for home care of alzheimer's disease patients using wireless sensor networks," in *Proceedings of International Workshop on Pervasive Technologies for the Support of Alzheimer's Disease and Related Disorders Sufferers*, 2007, http://heracleia.uta.edu/publicationbydate.html.
4. M. Rudafshani and S. Datta, "Localization in wireless sensor networks," in *Proceedings of the 6th International Symposium on Information Processing in Sensor Networks*, 2007, pp. 51-60.
5. K. Whitehouse, C. Karlof, and D. Culler, "A practical evaluation of radio signal strength for ranging-based localization," *ACM Mobile Computing and Communications Review*, *Special Issue on Localization*, Vol. 11, 2007, pp. 41-52.
6. K. Whitehouse, C. Karlof, A. Woo, F. Jiang, and D. Culler, "The effects of ranging noise on multihop localization: an empirical study," in *Proceedings of the 4th International Symposium on Information Processing in Sensor Networks*, 2005, pp. 73-80.
7. Y. Zhuang, L. Chen, X. S.Wang, and X. Lian, "A weighted moving average-based approach for cleaning sensor data," in *Proceedings of the 27th International Conference on Distributed Computing Systems*, 2007, pp. 38-38.
8. S. V. Vaseghi, *Advanced Digital Signal Processing and Noise Reduction*, 2nd ed., John Wiley & Sons, New York, 2000.
9. C. C. Chen, D. C. Mao, and C. Lee, "ART: A novel localization method for managing uncertainty region in wireless fading-signal sensor networks," *Ubiquitous Computing and Communication Journal*, Vol. 2, 2007, pp. 43-54.
10. M. L. Sichitiu, V. Ramadurai, and P. Peddabachagari, "Simple algorithm for outdoor localization of wireless sensor networks with inaccurate range measurements," in *Proceedings of the International Conference on Wireless Networks*, 2003, pp. 300-305.
11. D. Puccinelli and M. Haenggi, "Multipath fading in wireless sensor networks: measurements and interpretation," in *Proceedings of the International Conference on Communications and Mobile Computing*, 2006, pp. 1039-1044.
12. J. Y. Lee and R. A. Scholtz, "Ranging in a dense multipath environment using an

UWB radio link," *IEEE Journal on Selected Areas in Communications*, Vol. 20, 2002, pp. 1677-1683.
13. W. C. Chung and D. S. Ha, "An accurate ultra wideband (UWB) ranging for precision asset location," in *Proceedings of IEEE Conference on Ultra Wideband Systems and Technologies*, 2003, pp. 389-393.
14. A. Savvides, C. C. Han, and M. B. Srivastava, "Dynamic fine-grained localization in ad-hoc networks of sensors," in *Proceedings of the 7th Annual ACM/IEEE International Conference on Mobile Computing and Networking*, 2001, pp. 166-179.
15. N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, "The cricket location-support system," in *Proceedings of the 6th Annual ACM/IEEE International Conference on Mobile Computing and Networking*, 2000, pp. 32-43.
16. D. Niculescu and B. Nath, "DV based positioning in ad hoc networks," *Journal of Telecommunication Systems*, Vol. 22, 2003, pp. 267-280.
17. C. Y. Lin, W. C. Peng, and Y. C. Tseng, "Efficient in-network moving object tracking in wireless sensor networks," *IEEE Transactions on Mobile Computing*, Vol. 5, 2006, pp. 1044-1056.
18. I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Communication Magazine*, Vol. 40, 2002, pp. 102-114.
19. Texas Instruments, http://www.ti.com/.
20. C. S. R. Murthy and B. S. Manoj, *Ad Hoc Wireless Networks*: *Architectures and Protocols*, Prentice Hall PTR, New Jersey, 2004.
21. S. P. Kuo, Y. C. Tseng, F. J. Wu, and C. Y. Lin, "A probabilistic signal-strength-based evaluation methodology for sensor network deployment," *International Journal of Ad Hoc and Ubiquitous Computing*, Vol. 1, 2005, pp. 3-12.
22. TinyOS Community Forum, http://www.tinyos.net/.
23. H. Karl and A. Willig, *Protocols and Architectures for Wireless Sensor Networks*, John Wiley & Sons Ltd., 2005.
24. nesC: A Programming Language for Deeply Networked Systems, http://nescc.sourceforge.net/.
25. Sentilla | Moteiv Hardware Product Transition Notice, http://www.sentilla.com/moteiv-endoflife.html.
26. Y. M. Huang, D. C. Wang, and C. C. Chen, "A verification-based localization method for unstable radio sensor networks in smart home environments," in *Proceedings of the International Conference on Multimedia and Ubiquitous Engineering*, 2008, pp. 390-393.
27. F. Reichenbach and D. Timmermann, "Indoor localization with low complexity in wireless sensor networks," in *Proceedings of the International Conference on Industrial Informatics*, 2006, pp. 1018-1023.

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