# A Novel Method for Unstable-signal Sensor Localization in Smart Home Environments

Chao-Chun Chen[1], Ding-Chau Wang[2], Yong-Ming Huang[3]
[1]Dept. of Comp. Sci. & Info. Engr.
[2]Dept. of Info. Mgmt.
[3]Dept. of Info. & Comm.
Southern Taiwan University,
Tainan, Taiwan
*{chencc,zh9}@mail.stut.edu.tw, m95f0213@webmail.stut.edu.tw*

**_Abstract_**

*Wireless sensor networks receive much attention in these few years due to its wide spectrum of applications. Localization is one of the significant techniques in the ubiquitous sensor networks, and most localization techniques nowadays apply RSSI-based ranging techniques to compute the location of the object in wireless sensor network. However, a wireless sensor network is of a fading-signal environment that comprises noises, and the noises cause RSSI to become unstable and lead to abrupt distance estimates. In this paper, we propose Verification-Based Localization Method (VBLM) to alleviate the effect of the unstable signal and provide the high-accuracy location estimates in wireless sensor environments. The basic idea of VBLM is to prune noisy signals in the localization process. In our method, the sensor node would use another neighboring beacon to assist to verify the quality of received signal under acceptable communication cost, and thus, the noisy signals can be removed to avoid increasing the error in the localization. The experimental results show that VBLM indeed reduces the localization error in the unstable signal sensor networks than other localization methods.*

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

## 1. Introduction

Recent advance in the wireless sensor network have led to a vast and expeditious development in wireless sensor applications. In the 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 to support location-based services [1],[2],[3]. For instance, a remote home-care system in the smart-home environment would ask sensor nodes to obtain the geographical locations of children in order to understand the children status, such in the cradle or near the stairs. If the sensors detect a child near the warning area, e.g., stairs, the remote home-care system would notify the nursemaid to pay more care on the child.

Among the proposed technologies [4], the RSSI-based localization technique (RSSI stands for *received signal strength indication*) is the most applicable solution to the wireless sensor applications in the smart-home environment due to the low deployment cost. The RSSI-based methods adopt the transmission antenna to run the localization process, and thus, do not need any additional expensive hardware. In this way, popularizing the smart-home applications to each family then becomes feasible.

Although the RSSI-based localization technique is suitable for great amount of wireless sensor applications, the unstable radio signal brings a challenge to the localization in the smart-home environment [5],[6]. More specifically, when the antenna transmits network packets, the radio signal frequently become unstable [7], and the radio strength of packets become outlier in the statistic data. Hence, the effect of such the packet is like the noise in the signal processing [8], and taking such kind of packets into the localization process would reduce the accuracy. For example, the interference of furniture or movement of people or pets could easily produce the unstable radio signal in the smart-home environment. Therefore, the RSSI localization technique needs to consider the unstable-signal effect while it is applied to the smart-home environment.

Many small-area localization methods for the sensor networks have been proposed in the past years [4],[5],[9],[10]. However, the proposed RSSI-based localization methods do not consider the effect of unstable signal on distance measurement. Therefore, the past methods directly use the collected signals in their localization method, and thus, the unproofed signals increase the localization error in the real-world applications. In this paper, we propose the *Verification-Based Localization Method (VBLM)* to alleviate the effect of the unstable signal and provide the high-accuracy location estimate in wireless sensor environments. Assume the unknown node is the node that requests the localization, and a beacon node is the node that has known its own position and offer the function that translates a signal strength value (i.e., RSSI) to 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 understand whether a received signal is a noise, because no evidence can be used to approve the reliability of the received signal. Different from the traditional methods, in the proposed verification mechanism, the unknown node would use another neighboring beacon to assist to verify the quality of received signal. To the best of our knowledge, none of existing methods study the localization problem based on the collaboration of beacons.

In VBLM, once the beacon node receives the request message from the unknown node, it broadcast a ranging message so that the unknown node and another beacon node can simultaneously hear 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 redo the ranging process due to the interference of the unstable signal. Using such the verification mechanism, VBLM is able to prune most of the unstable signals, and delivers the reliable signals to the location calculation component. Although the verification mechanism needs more communication between nodes, we also show the communication cost for VBLM is still acceptable. We then conduct a set of real-world experiments to show the performance of the proposed method. Our experimental results show that VBLM is trustable in the unstable-signal sensor network by observing the reduction of the error of distance estimates and location estimates. Furthermore, the results show that VBLM indeed provides a higher accuracy than other localization methods without the verification mechanism.

The remaining sections of this paper are organized as follows. Section 2 describes the related work on the localization technologies. Next, we describe the system environment in Section 3. We present our proposed localization algorithm in Section 4. Then, Section 5 gives the experiment results. Finally, we conclude the paper in Section 6.

## 2. Related work

This section describes the localization techniques in wireless sensor network nowadays. The localization methods can be divided into two classes: range-based schemes and range-free schemes. The classification for the localization methods is shown in Fig. 1. The range-based schemes focus on that the sensor nodes have the ability to measurement of the distance or angle for 1-hop neighboring nodes. The range-based scheme includes RSSI [5],[9],[10], TOA [11],[12], TDOA[13],[14]. On the other hand, the range-free schemes focus on that the sensor nodes infer the distance between nodes according to the transmission information in the sensor network, such as hop-count messages [15]. The range-free scheme mainly includes DV-Hop [15].

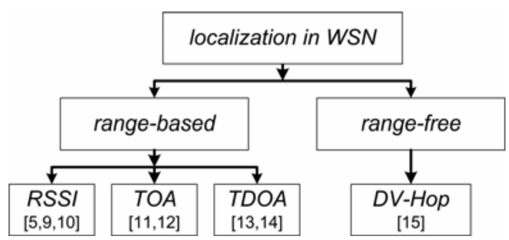


**Fig. 1. Classification of the localization techniques in the wireless sensor network.**

The received signal strength indication (RSSI) based localization techniques [5],[9],[10] read RF signal from a received packet, and use the information to estimate locations. The RF signal attenuates as the 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, thus, the advantage is low cost on deployment and energy consumption. However, RF signal is easily interfered by the noises in the wireless environment, and the corresponding RSSI values become unstable. Consequently, sensor could generate large error from reading RSSI values. Some methods [7] proposed for cleaning sensor readings are based on temporal statistics, however, localization techniques need the signals occurred at the same timestamp. In this paper, we focus on the property of localization techniques, and propose an efficient localization method considering the cleaning of the noisy signals.

Time of arrival (TOA) techniques [11],[12] apply the time that a packet travels 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 the energy consumption, computational power, and environment limitations, the synchronization for all sensors is still a severe research challenge in wireless sensor networks. Time difference of arrival (TDOA) based techniques [13],[14] improve the inconveniences of TOA. TDOA simultaneously sends a radio signal and an ultrasound pulse to the receiver. Base on the difference in traveling speeding of two types of message, the receiver is able to estimate the distance by observing the time difference of the message arrival. The comparisons between the TOA(and TDOA)-based technique and the above mentioned RSSI-based technique are shown in Table 1.

**Table 1. A comparison of RSSI-based and TOA(TDOA)-based localization.**

| | RSSI-based | TOA(TDOA)-based |
|---|---|---|
| challenge | shadowing, fading, multipath, environmental obstacles | interference, multipath, envir onmental obstacles |
| time synchroniza tion | none | highly depend on synchroniz ation of the sensor nodes |
| hardware require ment | none | need additional hardware (e. g., ultrasound transceiver) |
| deployment cost | low | high |
| energy consumpt ion | low | high |

Range-free DV-Hop [15] estimates distance based on inference, instead of directly measuring the distance. DV-Hop evaluates the distance between two nodes as multiplication of the number of hop counts and the average distance of a hop. Thus, the distance of two nodes is basically inferred from the geometry relationship 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 the range-based techniques. Especially, 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 are those that 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, e.g., $Euclidean(B_1,B_2)$ in the figure. Unknown nodes are those that need to request for their current locations, e.g., $U$ in the figure. In many scenarios of smart-home applications, the unknown nodes represent the moving objects in the sensor network [16].

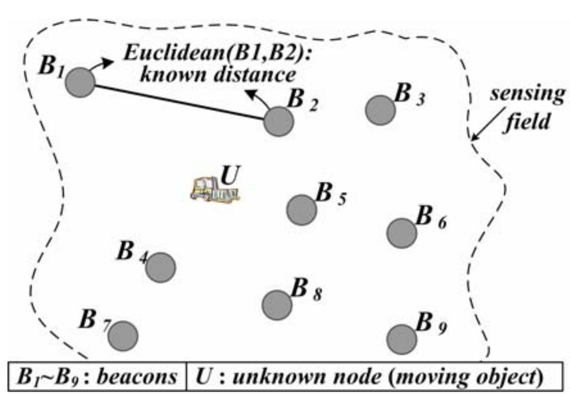


**Fig. 2. Illustration of wireless sensor environment.**

In general, a sensor node has four major components: the sensing unit, the processing unit, the communication unit, and the power unit [17]. For the scope of the paper, the communication unit and the processing unit are the most important components in the localization process. The communication unit equips with an antenna and is used to send or receive RF messages through the antenna. The communication component also has an analog-to-digital converter (ADC) to recognize the received signal strength indication (RSSI) of a received message. Some common chipset for the up-to-date sensors include ChipCon CC1000, ChipCon CC2420 [18], etc. The communication component can operate on over 30 transmission power levels and multiple transmission frequencies. The different settings of the communication component can vary 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 distances are stored in the memory of the wireless sensor. While a 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 will 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 would use another neighboring beacon to assist to verify the quality of received signal, and thus, the noisy signals can be removed to avoid increasing the error in the localization. Fig. 3 depicts the idea of VBLM. Assume $B_1$ 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, -62*dBm* and -60*dBm* 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, and obtained 100*cm* (because RSSI(-62*dBm*)=100*cm*). Since the estimated distance *Estimate*($B_1$,$B_2$) equals to the reference distance between $B_1$ and $B_2$, *Euclidean*($B_1$,$B_2$), that is computed from the pre-trained beacon positions, we thus treat the signal of the ranging-request message is reliable. Notice that the distance error is set to 0*cm* in this example for easily understanding our idea. As the signal is reliable, $B_1$ continues to evaluate distance *Estimate*($B_1$,$U$) by looking up the signal-matching table, and obtain 80*cm* (because RSSI(-62*dBm*)=100*cm*). Finally, $B_1$ reports *Estimate*($B_1$,$U$)=80*cm* to $U$.

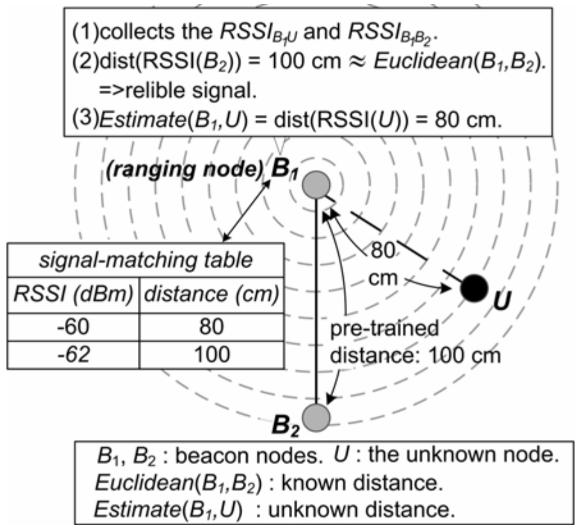


**Fig. 3. Illustration of the basic idea of the VBLM**.

The flow diagram of VBLM consists of three stages, and is depicted in Fig. 4. The first stage is to apply the signal matching model to build a signal-matching table, as shown in the left side of the figure, for each beacon. A beacon that equips with the signal-matching table has the capability of translating RSSI values to distance estimates. The second stage is the Verification-Based Ranging Algorithm (VBRA), which handles the ranging task, and VBRA is the most 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 again. 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 distance from at least three beacons, the location can be estimated. The details of the three stages are presented in the following three subsections.

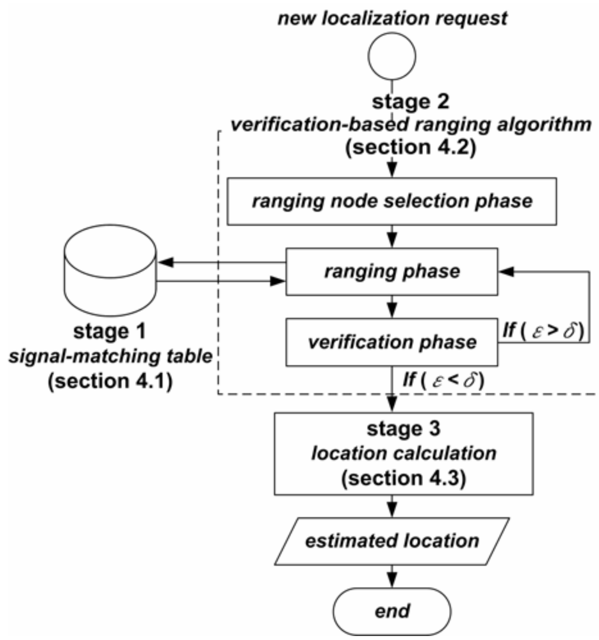


**Fig. 4. VBLM flow diagram.**

### 4.1. Signal-matching table

The signal-matching table is design to match possible distances for a given RSSI, and 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 [19] cannot adequately represent the multi-path effect in the 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 during running the ranging algorithm that will be discussed in Section 4.2.

In order to build the signal-to-distance table, RSSI values at different distances need to be collected and organized. The flow diagram of building the signal-to-distance table is illustrated in Fig. 5. Firstly, 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 then starts to collect RSSI values at every 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.

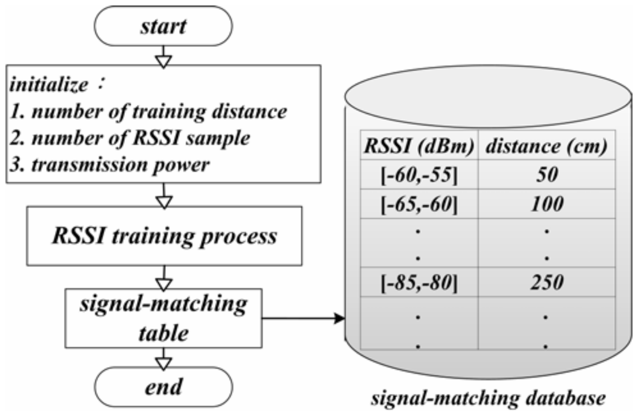


**Fig. 5. The flow diagram of building the signal-to-distance table.**

### 4.2. Verification-based ranging algorithm (VBRA)

Fig. 6 shows Verification-based Ranging Algorithm (VBRA). The algorithm includes three phases: (i) ranging node selection phase, (ii) ranging phase, and (iii) verification phase, and the three phases are presented in details as follows.

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**Verification-based Ranging Algorithm**

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Input:
*U*: denotes the sensor node *U* that issues to the ranging request; // i.e., unknown node.
$\delta$: 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 returns 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 $B_m$.
//$\delta$ is pre-defined error threshold.
Step 7: $B_n$ computes the $dist(B_n, B_m)$;
Step 8: $\varepsilon = | dist_m(B_n, B_m) - dist(B_n, B_m) |$;
Step 9: if ($\varepsilon > \delta$) then
    goto Step1;
  else
    $B_n$ converts $RSSI_S$ to $dist_m(B_n, U)$;
    return $dist_m(B_n, U)$;
  endif

---

**Fig. 6. Verification-based Ranging Algorithm (VBRA).**

#### 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 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. This is because in many practical experiences [5], the greater RSSI value has lower probability to incur noise.

The steps of this phase are shown in Step 1~Step 3 in Fig. 6. 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, and the steps are shown in Step 4~Step 6 in Fig. 6. The ranging node starts by broadcasting a ranging message to 1-hop neighboring nodes. Notice that the 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 is 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 depicted in Step 7~Step 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 $\varepsilon$ between the absolute and estimated distances for the beacon node. If the error $\varepsilon$ is less than the error threshold $\delta$, the ranging node sends the distance estimate to the unknown node. Otherwise, VBRA discards the current distance estimate and generates the next distance estimate. The process is stopped when the condition $\varepsilon<\delta$ is met.

The parameter, error threshold $\delta$, in the algorithm is pre-determined by the system administrator according to the real environment. If the error threshold $\delta$ is too large, then the verification mechanism cannot filter the abrupt signal. In this case, VBRA degrades to the traditional ranging methods. On the other hand, if the error threshold $\delta$ is too small, VBRA would frequently abort the ranging result due to the strict restriction on achieving the error threshold $\delta$. In this case, the sensor network would waste much additional cost on computation and communication. Hence, setting a sophisticated value for the error threshold $\delta$ is important for VBRA. Since the error threshold $\delta$ is sensitive to the physical environments, it is hard to derive a general rule to setting the error threshold $\delta$. Some literature [5] offers practical experiences, and it could help the system administrator increase the familiarity on the deployed environment.

The pack size used in the communication is economic in the VBRA. Fig. 7 illustrates the packet format for the unknown node and beacons. The packet consists of four attributes, including Destination, RSSI, Source, and Location. The size of the packet is 11 bytes and much less than the default packet size (40 bytes) in the TinyOS system [20]. Each attribute is explained as follows. The first attribute, Destination, records the ID of the ranging node. The second attribute, RSSI, has 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 the location marked as null stands for the unknown node.

| RSSI message from *U* | | | | RSSI message from $B_2$ | | | |
|---|---|---|---|---|---|---|---|
| destination | RSSI | source | location | destination | RSSI | source | location |
| $B_1$ | $RSSI_U$ | $U$ | *null* | $B_1$ | $RSSI_{B2}$ | $B_2$ | $(X_2, Y_2)$ |

**Fig. 7. The message format in VBRA.**

### 4.3. Location calculation

Since the distance measurements could be inexact accurate, the location of the unknown node is uncertain and bounded in a region [9], as shown in 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.

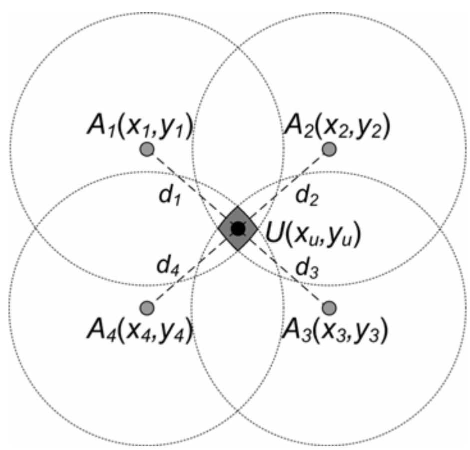



**Fig. 8. Illustration of the possible region of location calculation.**

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

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

In order to solve the location of node U, the above equations can be transformed into the matrix form as follows.

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

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

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

$$U=\begin{bmatrix} x_u \\ y_u \end{bmatrix} .$$

We use a simple example to demonstrate the above equations for the location calculation. Assume $A_1(x_1,y_1)$=(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 the distances between the unknown node $U$ and the beacons are d1=d2=d3=d4=6. Then, Equation (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 Equation (3), the location of unknown node ($x_u$, $y_u$) is obtained as (4,3.5).

### 4.4. Interaction Analysis among Nodes

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

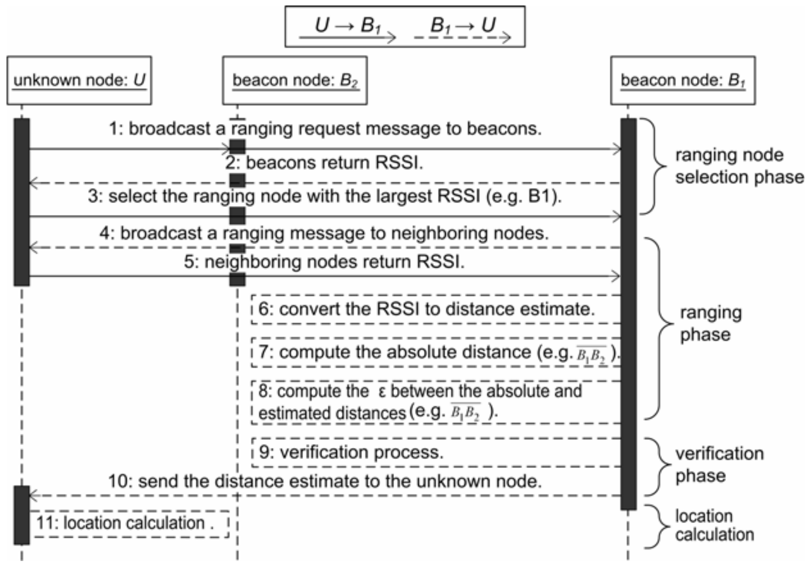



**Fig. 9. The sequence diagram of VBLM.**

### 4.5 Discussions

VBLM has four advantages. Firstly, our proposed technique offers distance estimate verification. Secondly, the VBLM is also be easily implemented. Moreover, users can set their error threshold according to the different application needs in various environments. Lastly, VBLM provides more reliable distance estimate. During the experiments, we found that VBLM is able to filter the environmental noise that affect the quality of RSSI. Therefore, VBLM can generate more reliable distance estimates.

VBLM can also be adopted in various RF signal-based ranging techniques, which includes TOA, TDOA, RSSI, and etc. In this paper, we implement VBLM using RSSI because the hardware is cheap and widely used in many sensor applications. However, the proposed method is basically quite extensive.

## 5. Experiment results

This section provides a detailed quantitative analysis to verify our proposed method, including performance study of VBLM, as well as the comparisons with the trilateration algorithm and the multilateration algorithm [21] that do not deal with the unstable signal.

The system prototype implemented for the experiment study is designed by the sensor programming language, nesC [22] on Tmote Sky motes [23]. The prototype is an extension from our previous work [9], [24]. We run the experiments in the campus of Southern Taiwan University to obtain the real-world results for performance study. In the default settings, the error threshold is set to 50*cm*, and four beacons are used on average in the localization which setting is similar to [25][26]. The four-beacon deployment is almost the minimal scale for a sensor localization system, thus, our experiment performance can be treated as the benchmark under the poor-resource scenarios. Hence, VBLM should have better performance in the larger-scale deployment than this experiment setting. Finally, the setting of obstacles is an imitation of the experiments in [5].

### 5.1. Characterizing the 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. Fig. 10 illustrates the RSSI values for different settings of the transmission power in various distances (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 around from 200*cm* to 560*cm*, and the curve of 0*dBm* can transmit messages with the longest distance. Hence, in the rest of the experiments, we set the transmission power to 0*dBm*, the maximal ranging distance to 500*cm*, and the maximal localization area to 500x500$cm^2$.

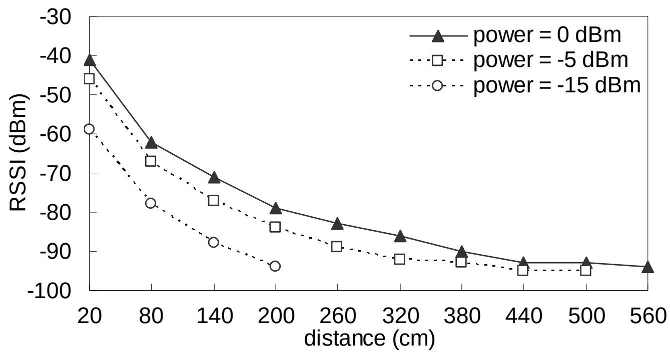


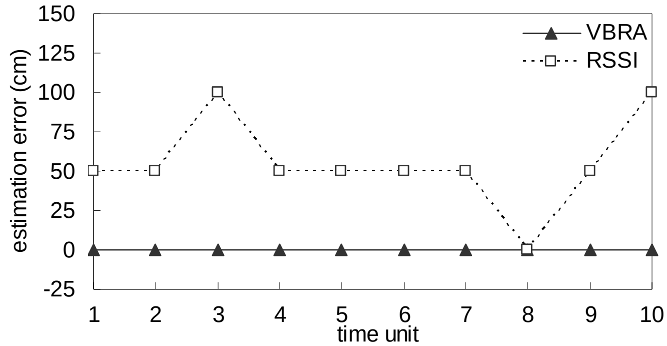

**Fig. 10. The RSSI values of different settings of transmission power.**

### 5.2. Effect of noises on distance estimations

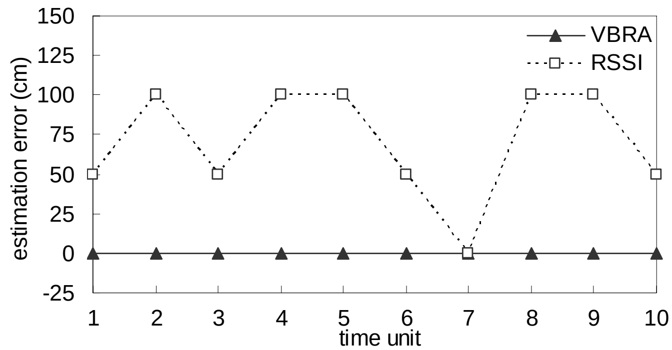
In order to evaluate the validity of VBRA in environmental interference, we conduct an experiment for comparing the distance estimations between VBRA and the traditional RSSI ranging algorithm [10]. We emulate the interference of noises by placing a carton in the middle between the unknown node and the beacon node.

The Fig. 11 illustrates the comparison for different distances (i.e., from 100*cm* to 500*cm*) in the noisy environment. Observing curves from the results, VBRA performs much better than the traditional RSSI ranging algorithm in various situations (i.e., Fig. 11(a) ~ Fig. 11(c)). The reason is that VBRA successfully identifies the signal affected by the obstacle. Hence, VBRA can filter the interference of noises on RSSI.

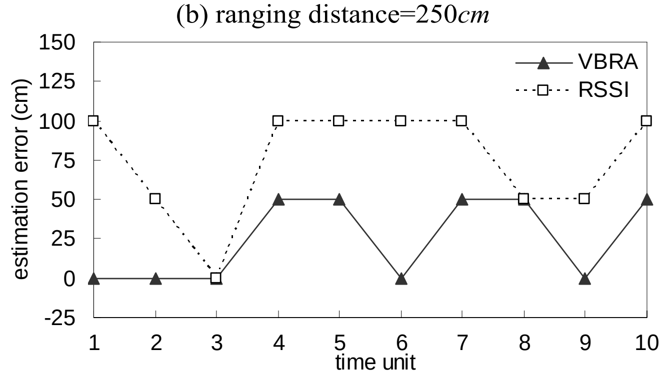
In addition, we also observe that the effect of the environmental noise increases as the increasing ranging distance, and the noise affects both algorithms. For example, in the RSSI ranging algorithm, the number of time units that obtain the estimation error over 100*cm* for three experiments are two, five, and six, respectively. On the other hand, the noise do not affect VBRA, as shown in Fig. 11(a) and Fig. 11(b). And only five time units are affected in the Fig. 11(c). Thus, VBRA is more accommodative than the RSSI ranging algorithm in the noisy environment.




(a) ranging distance=100*cm*




(b) ranging distance=250*cm*



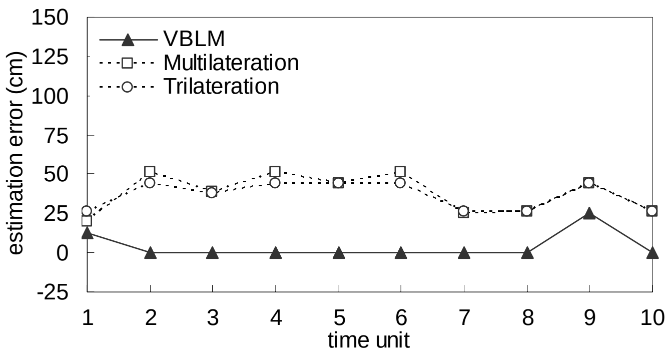

(c) ranging distance=500*cm*

**Fig. 11. Comparisons between VBRA and traditional RSSI ranging algorithm for different distances.**

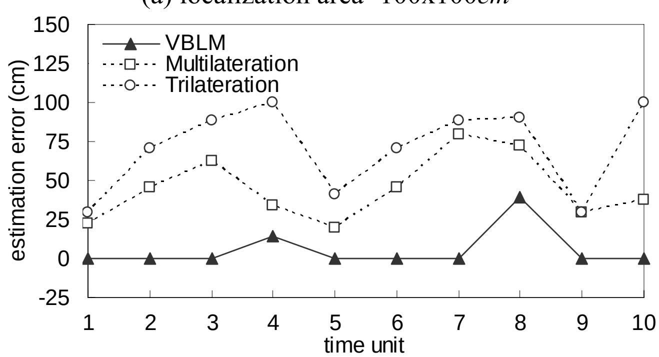
### 5.3. Effect of noises on localization

In order to evaluate the accuracy of VBLM in environmental interference, we next design an experiment for comparing the estimation error among the three localization methods, including VBLM, the multilateration algorithm [21], and the trilateration algorithm [21]. The interference of noises is simulated as the previous experiment. The results for these three algorithms are shown in Fig. 12. From the result, VBLM obtains lower estimation error than other two algorithms. This is because that VBRA filters most unstable signals. Hence, VBLM can obtain high-accuracy locations in unstable-signal sensor environment. In contrary, the estimation error of other two algorithms, the multilateration algorithm and the trilateration algorithm, varies with time units since the two algorithms directly use the unreliable signal to calculate locations. Thus, the verification mechanism successfully improves the location accuracy.

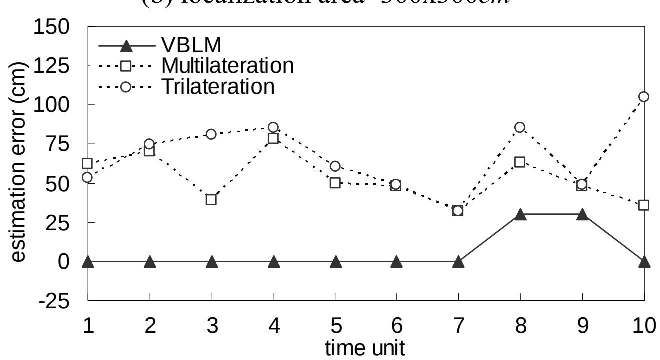
Similar to the last experiment, the effect of the environmental noise increases as the increasing localization area. The larger localization area implies the larger ranging distance between the beacon and the unknown node. According to the results in the last experiment, the large ranging distance would produce the distance estimates with large estimation error, and these distance estimates are then delivered to each localization method to produce worse location estimates.




(a) localization area=100x100$cm^2$




(b) localization area=300x300$cm^2$




(c) localization area=500x500 $cm^2$

**Fig. 12. Comparisons of localization error in different areas.**

### 5.4. Effect of the number of beacons

In the last experiment, we study the effect of number of beacons in different localization method, and the result is shown in Fig. 13. In the ideal environment, the location calculation with the more beacons would obtain locations with higher accuracy. An interesting point in the figure is that the mulateration algorithm with four beacons does not perform better than that with three beacons. The reason is explained as follows. In the noisy environment, using more beacons would increase probability of employing the ranging results with large distance error in the location calculation. Thus, using more beacons in localization is not necessary to obtain higher accuracy in the unstable-signal sensor networks.

Compare to the multilateration algorithm, VBLM is designed to aggressively filter noisy signals in the ranging stage (i.e., using VBRA). Hence, the high-accuracy distance estimates are delivered to VBLM to obtain high-accuracy locations.

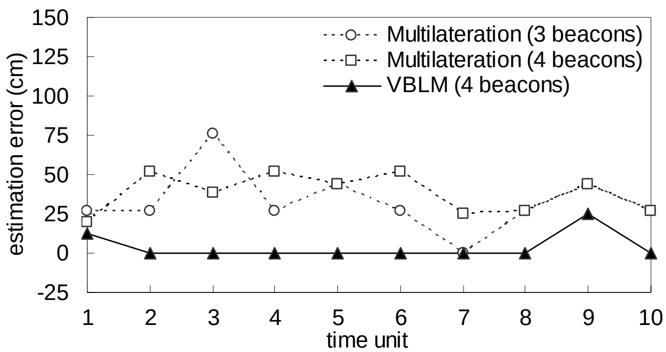



**Fig. 13. Estimation error for different number of the beacons.**

## 6. Conclusions and future work

The localization is a critical technique of the wireless sensor applications in the smart-home environment. However, previous RSSI-based localization methods do not consider the effect of the unstable RF signal, and thus, the positioning accuracy decreases. In this paper, we propose the verification-based localization method (VBLM) to improve the positioning accuracy in the unstable-signal wireless sensor network. VBLM can verify the reliability of distance estimates during the ranging process, such that the system generates more reliable ranging results. Furthermore, we design an error control solution for user to determine the degree of accuracy by setting the error threshold. Our future work will continue study more detailed factors, such as failure ratio of localization, the relationship between the error threshold and the estimation error, etc. After the study, we plan to extend the work to investigate another localization challenge, the irregular broadcasting effect of the sensor antenna, in the smart-home environment.

## 7. Acknowledgment

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## Authors

**Chao-Chun Chen** is an assistant professor in the Department of Computer Science and Information Engineering, Southern Taiwan University (STUT), Taiwan. He received the PhD degree in the Department of Computer Science and Information Engineering at National Cheng-Kung University, Taiwan, 2004. Before joining STUT, he was an assistant professor in Shih-Chien University Kaohsung Campus. He has served as a member of Editorial Board in the special issue "Future Generation Smart Space" of International Journal of Smart Home (IJSH). His research interests include mobile/wireless data management, sensor technologies and applications, spatio-temporal databases, and computational geometry. He has published dozens of papers in prestigious journals and conferences, including IEEE Transactions on Knowledge and Data Engineering (TKDE), Wireless Networks (WINET), GeoInformatica Journal, Distributed and Parallel Databases, Performance Evaluation, International Symposium on Advances in Geographic Information Systems (ACM GIS), International Conference on Distributed Computing Systems (ICDCS), International Conference on Mobile Data Management (MDM), and International Conference on Database Systems for Advanced Applications (DASFAA).

**Ding-Chau Wang** received the B.S. degree from Tung-Hai University, Taichung, Taiwan, and the M.S. and Ph.D. degrees in computer science and information engineering from National Cheng Kung University, Tainan, Taiwan. He is currently an assistant professor in the Department of Information Management at Southern Taiwan University. His research interests include distributed systems, mobile computing, sensor network, and performance analysis.

**Yong-Ming Huang** received the B.S. degree in information management from the Hsing Kuo University of Management, Tainan, Taiwan, in 2006, and M.S. degree in information communication from Southern Taiwan University, Tainan, Taiwan, in 2008. His research interests include wireless sensor networks and genetic algorithm.