The Beacon Movement Detection Problem in Wireless Sensor Networks for Localization Applications

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Abstract—Localization is a critical issue in wireless sensor networks. In most localization systems, beacons are being placed as references to determine the positions of objects or events appearing in the sensing field. The underlying assumption is that beacons are always reliable. In this work, we define a new *Beacon Movement Detection (BMD)* problem. Assuming that there are unnoticed changes of locations of some beacons in the system, this problem concerns how to automatically monitor such situations and identify such unreliable beacons based on the mutual observations among beacons only. Existence of such unreliable beacons may affect the localization accuracy. After identifying such beacons, we can remove them from the localization engine. Four BMD schemes are proposed to solve the BMD problem. Then, we evaluate how these solutions can improve the accuracy of localization systems in case there are unnoticed movements of some beacons. Simulation results show that our solutions can capture most of the unnoticed beacon movement events and thus can significantly alleviate the degradation of such events.

Index Terms—Context awareness, localization, location-based service, pervasive computing, positioning, wireless sensor network.

1 Introduction

Recently, we have seen significant progress in the areas of wireless ad hoc and sensor networks. Ad hoc networking technologies enable quick and flexible deployment of a wireless communication platform. A wireless sensor network typically adopts the ad hoc communication architecture and is capable of exploiting context information collected from sensors. Many applications of wireless sensor networks have been proposed [2], [5], [6].

Sensor networks are promising because they support context-aware and location-aware services. The success of this area may greatly benefit human life. One essential research issue in sensor networks is *localization*, whose purpose is to determine the position of an object or event. In most localization systems, they assume that there are sets of *beacon sensors* (or simply *beacons*), which may or may not be aware of their locations and can periodically transmit/receive short broadcast packets. By evaluating the distances, angles of arrival, or signal strengths of these broadcast packets, we can estimate the locations of objects by triangulation [24] or pattern matching [3]. Under such an architecture, we observe that most existing works have an underlying assumption that beacons are always reliable. Based on this observation, this paper points out a new *Beacon Movement Detection* (BMD) problem that may occur in most beacon-based localization systems. No matter if beacons know or do not know their own locations, we define a *beacon movement event* as one where a beacon is migrated to a location different from where it is supposed to be (or where it was at the training stage). However, our localization system is unaware of this event. With unnoticed beacon movement events, the topology of the sensor network may be different from what it is supposed to be, and thus a localization algorithm may lose its accuracy or even incorrectly estimate an object's location. In this work, we assume that beacons are static under normal circumstances, but occasional beacon movement events are not unusual. This is true especially in a wireless sensor network. For example, a beacon node may be moved by unexpected forces, such as those from animals being monitored, or by manual errors, because beacon nodes are normally quite tiny.

The BMD problem involves two issues. First, we need to determine those beacons that are unexpectedly relocated. Second, the result has to be forwarded to the positioning engine to reduce the impact of movement on localization accuracy. To solve the first issue, we will allow beacons to monitor each other to identify those moved beacons automatically. This is nontrivial work because we do not have a trust model among beacons. In this paper, we show that without any assumption, it is impossible for a general BMD problem to correctly identify those moved beacons because an ambiguity situation will always exist. However, if we assume that the number of moved beacons is relatively small, we can relieve the BMD problem using some

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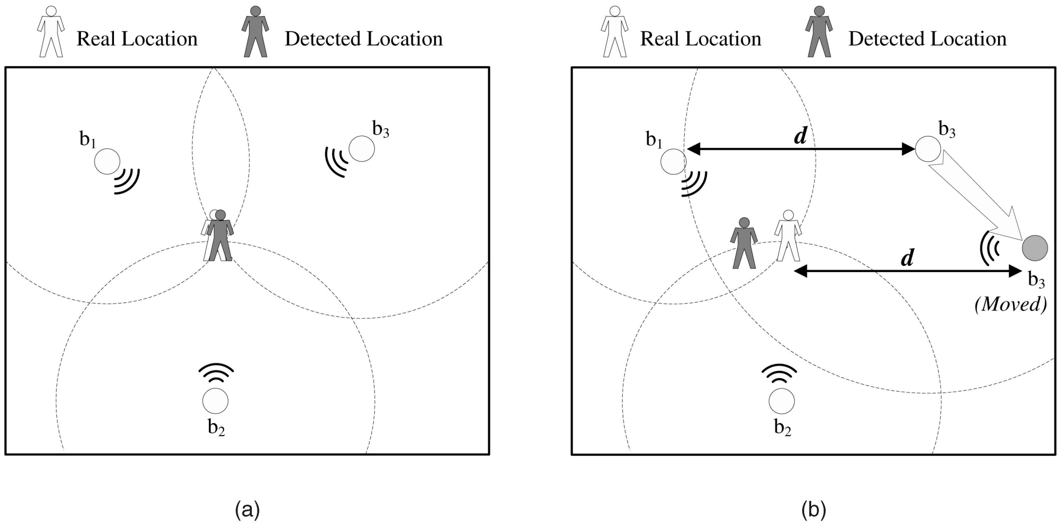

Fig. 1. An example of the BMD problem.

heuristic algorithms. Based on this assumption, we propose four schemes. The first *location-based* (LB) scheme tries to calculate each beacon's current location and compares the result with its predefined location to decide if it has been moved. In the second *neighbor-based* (NB) scheme, beacons will keep track of their nearby beacons and report their observations to the *BMD engine* to determine if some beacons have been moved. In the third *signal strength binary* (SSB) scheme, the change of signal strengths of beacons will be exploited. In the last *signal strength real* (SSR) scheme, the BMD engine will collect the sum of reported signal strength changes of each beacon to make decisions. Note that only the first scheme assumes that the original locations of beacons are known in advance. The other three schemes do not assume any a priori knowledge on the original locations of beacons.

The noise-prone signal strengths are another challenge to the BMD problem. In real environments, signal strengths may be influenced by many factors, such as hardware difference, remaining battery, multipath propagation, and dynamic signal fading. When combining these factors, it is even harder to correctly determine a beacon movement event. To relieve this influence, we import the concept of *tolerable regions* in the proposed schemes. To evaluate the proposed BMD schemes, we adopt a close-to-reality *radio irregularity model (RIM)* [28] to simulate the decay of signal strengths. This model has been shown to be able to reflect the propagation of radio signals, especially in indoor environments. In our simulation study, we have tuned the parameters of RIM to evaluate the performance of LB, NB, SSB, and SSR under different conditions. The results show that the SSB and SSR schemes perform well under most situations. The NB scheme is easy to implement but has limited movement detection capability. Compared to SSB, SSR, and NB, the LB scheme has higher computation complexity and is quite sensitive to the density of beacons. When there are many beacons, LB can have excellent detection results. However, its performance degrades quickly when there are not enough beacons to provide a good localization service.

The remainder of this paper is organized as follows: Section 2 gives a formal definition of the BMD problem. Related works and motivations are given in Section 3. Section 4 presents our solutions to the BMD problem. Then, in Section 5, we evaluate the proposed schemes and examine their capability to improve the localization accuracy in events of beacon movement. Finally, Section 6 draws our conclusions.

2 Problem Definition

Before we formally define the BMD problem, we illustrate an example to demonstrate how movement of some beacons may affect the accuracy of localization results. Let us consider Fig. 1a, where we use three beacons to determine a target's position via typical triangulation approaches. If beacon b_3 is moved to the location marked in gray without being noticed, the system may incorrectly estimate the target's location, as shown in Fig. 1b. Note that the circle centered at b_3 has a radius equal to the distance from the real location of b_3 to the target. Also note that the results proposed in this paper are applicable not only to the unnoticed movement of beacons, but also to the unexpected behaviors of some beacons (for example, a beacon may be unexpectedly covered by an obstacle, thus lowering the observed signal strengths).

We are given a sensing field, in which a set of beacons $B = \{b_1, b_2, \ldots, b_n\}$ is deployed for localization purposes. Depending on different schemes, we may or may not assume that the locations of these beacons are known in advance. Periodically, each beacon will broadcast a HELLO packet. To determine its own location, an object will collect HELLO packets from its neighboring beacons and send a signal strength vector $S = [s_1, s_2, \ldots, s_n]$ to an external positioning engine, where s_i is the signal strength of the HELLO packet from b_i. If it cannot hear from b_i, we let $s_i = s_{min}$, where s_{min} denotes the minimum signal strength and any signal strength lower than this value is not detectable by a receiver. The positioning engine can then estimate the object's location based on S (for example, in the

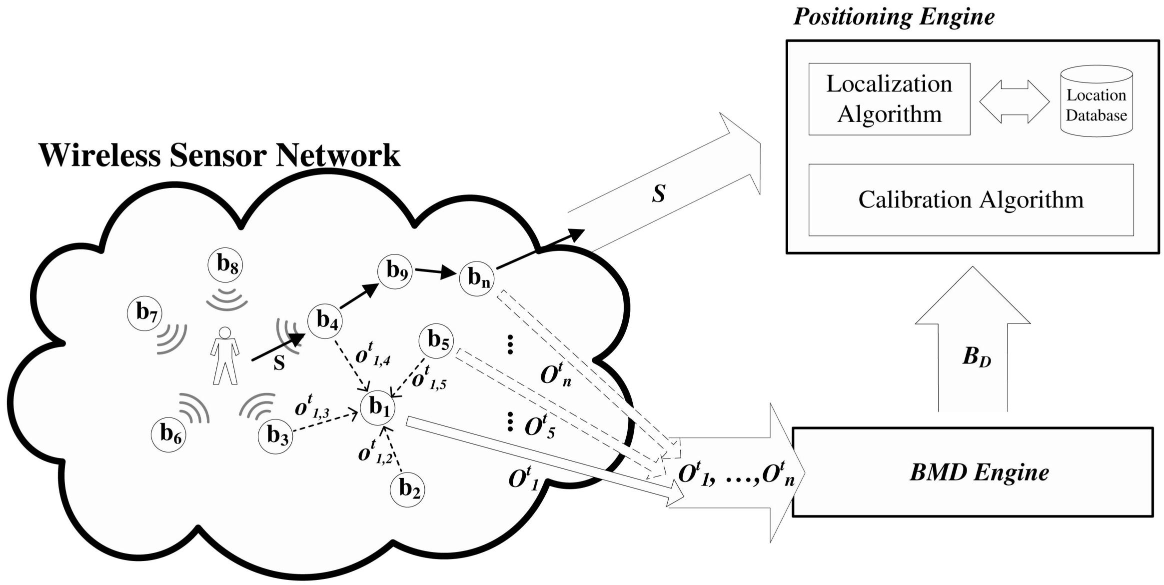

Fig. 2. The system model.

case of RADAR [3], S is compared against a location database obtained in the training phase based on a pattern-matching method).

Suppose that a set of unreliable beacons $B_M \subset B$ is moved or blocked by obstacles without being noticed. The BMD problem is to compute a detected set B_D that is as similar to B_M as possible. The result B_D may be used to calibrate the positioning engine to reduce the localization error (for example, in the case of RADAR, the entry s_i in S may be ignored if b_i is detected to be unreliable).

To solve the BMD problem, we will enforce beacons to monitor each other from time to time. Let us denote the local *observation vector* of b_i at time t by $O_i^t = [o_{i,1}^t, o_{i,2}^t, \ldots, o_{i,n}^t]$, where $o_{i,j}^t$ is b_i's observation on b_j at time t. The content of an observation will depend on the corresponding BMD scheme (refer to Section 4). We use the observation vector at time $t = 0$ to represent the original observation where all beacons stay at their original locations. The *observation matrix* at time t is denoted by $O^t = [O_1^t, O_2^t, \ldots, O_n^t]^T$. Note that ideally the observation matrix O^t should be symmetric (in the sense that $O^t[i,j] = O^t[j,i]$). However, in practice, due to the asymmetry of radio propagation, it is possible that O^t is asymmetric (our BMD schemes are able to handle asymmetric O^t). Given O^t, the BMD engine is capable of calculating a set B_D. The result is then sent to the calibration algorithm in the positioning engine. Fig. 2 illustrates our system model.

Considering the following reasons, we define the *tolerable region* R_i of each beacon b_i as the geographic area within which a slight movement of b_i is acceptable. First, radio signal tends to fluctuate from time to time. Second, slight movement of a beacon should not change the signal strength much unless an obstacle is encountered (if so, this should be discovered by our BMD engine). Third, ignoring the data of a slightly moved beacon in the location database will decrease the localization accuracy due to fewer beacons helping the localization procedure. So the slight movement of beacons is constrained by the tolerable regions. As a result, the unreliable set B_M only contains those beacons which are moved out of their tolerable regions. The sizes of tolerable regions are application dependent, which is beyond the scope of this work. For simplicity, tolerable regions are assumed to be circles centered at beacons of the same radius.

3 Related Works and Motivations

There are two main approaches for localization: multilateration and pattern matching. Multilateration is a process of finding the location of an object based on measuring the distances or angles of three or more signal sources at known coordinates. A special case of multilateration is triangulation. For example, the Bat sentient system [1] is composed of a set of sensors for 3D localization. Sensors are installed at known positions, such as ceilings, to measure the signal traveling time from a user badge to them. Then, a triangulation algorithm calculates the location of the badge. Localization by the signal's angle of arrival is addressed in [17], [20], [21]. In Cricket [21], ultrasonic sensors are used to estimate the location and orientation of a mobile device. In [24], a distributed positioning system called Ad Hoc Localization System (AHLoS) is proposed, where some beacons are aware of their own locations while others are not. The former are used to determine the positions of the latter. A similar work based on a probability model is proposed in [22].

All the above systems require special hardware to support localization. Recently, indoor localization, using pattern-matching techniques [3], [4], [14], [23], [25], is gaining popularity because the localization task can be achieved by off-the-shelf communication hardware, such as WiFi-enabled mobile devices. Such localization systems are more cost-effective. Pattern-matching localization does not rely on any range estimation between mobile devices and infrastructure networks. For example, a system can be based on WiFi access points at unknown locations to serve as beacons [3]. Then a training phase is exploited to learn the possible signal strengths of these beacons at locations of our interest. The training results will be stored in a location database. Then, in the positioning phase, an object to be localized will compare the strengths of received signals against the location database to estimate its location. Extensive research has been dedicated toward this direction [7], [9], [12], [13], [14], [19], [25].

While the above works assume that beacons are static, some works have considered mobile beacons [16], [18], [22], [26]. It is typically assumed that a mobile beacon cannot only move around but also locate itself through a special device or mechanism. With periodic broadcast, these mobile beacons can also help conduct localization. The trajectory of the locations where broadcast messages are sent can be regarded as a sequence of static sensors.

All the above works assume that beacons are reliable. In reality, some beacons may be moved to locations where they are not supposed to be without being noticed. Some beacon signals may be blocked by new obstacles deployed after the training phase, making their signal strengths untrustworthy. Some beacons may even conduct malicious attacks if they are compromised. To address the reliability issue, Olson et al. [18] mention the concept of beacon movement. The authors propose using a powerful mobile device to relocate those moved beacons. How to detect malicious beacons in a localization system is addressed in [15], [27]. A malicious beacon is one which is tampered or compromised by an adversary and which can provide false distance or angle measurements. A malicious attack can be conducted individually or cooperatively. In this work, we do not consider intelligent malicious beacons. Instead, we assume that beacons are tiny and lightweight. The major sources of unreliability come from unnoticed movement of some of these tiny beacons or unnoticed deployment of obstacles after the training phase, which may lower some beacons' signal quality. However, signal quality from beacons can always be correctly measured, unless they are being interfered by noise. Based on these assumptions, we discuss our BMD problem.

4 Beacon Movement Detection Algorithms

To solve the BMD problem, we propose four detection schemes, namely *LB*, *NB*, *SSB*, and *SSR* schemes. These schemes differ in their local processing rules of beacons and the corresponding decision algorithms at the BMD engine. In the LB scheme, each beacon reports its observed signal strengths, which are used by the BMD engine to compute each beacon's current location. The result is used to compare against its original location. In the NB scheme, each beacon locally decides if some neighboring beacons have moved into or out of their communication coverage range and reports its binary observations to the BMD engine. The SSB scheme is similar to the NB scheme, but the definition of movement is according to a threshold of signal strength change. In the SSR scheme, a beacon does not try to determine whether a neighboring beacon has been moved or not. Instead, each beacon reports the amount of signal strength change of each neighbor; the sum of all reported values is used by the BMD engine to make a global decision.

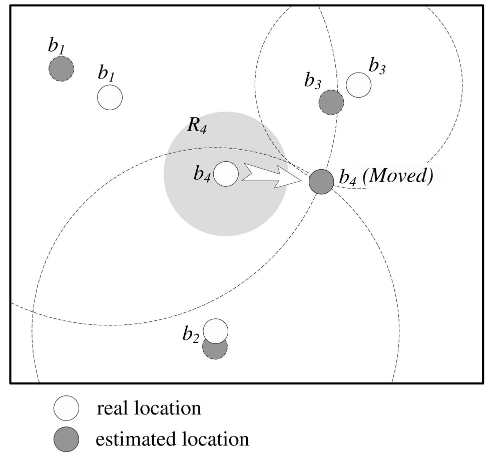

Fig. 3. An example of movement detection in the LB scheme where b_4 is the only beacon being moved. A trilateration technique is used in this example.

4.1 Location-Based Scheme

The LB scheme assumes that the initial locations of beacons are known by the BMD engine in advance and utilizes localization techniques to monitor the locations of beacons. Techniques such as trilateration or pattern matching can be used in the BMD engine. Each beacon is in charge of reporting the observed signal strength values of its neighbors to the BMD engine. Hence, the observation $o^t_{i,j}$ is defined as $o^t_{i,j} = s^t_{i,j}$, where $s^t_{i,j}$ is the observed signal strength by b_i on b_j. The engine then estimates the position of each beacon through any localization technique. Let the estimated location of b_j at the current time t be ℓ^t_j. Then the tolerable region R_j will be used to decide whether b_j has been moved. If ℓ^t_j is out of the tolerable region R_j, then b_j is determined to be unreliable.

An example using the trilateration technique is shown in Fig. 3. Beacon b_4 is moved out of its tolerable region R_4. Since beacons b_1, b_2, and b_3 are unmoved, they can help to determine b_4's new location. One point worth mentioning is that because of b_4's movement, the estimated locations of b_1, b_2, and b_3 may also be changed by a certain degree. So the outcome depends on the observations of the beacons in B_M. Intuitively, the LB scheme is sensitive to the performance of the adopted localization system. If the density of beacons is too low or signal strengths are too unstable, the results of movement detection cannot perform well.

Since this scheme uses beacons (including unreliable ones) to localize each other, moved beacons will also contribute some errors to the mutual localization process and thus influence our decisions. Here we propose to use a simple greedy approach as follows. After the BMD engine receives the observations from all beacons, it estimates their possible locations under current mutual observations. Then the beacon b_i with the longest moved distance will be selected. If b_i's current location is out of its tolerable region, it will be included in B_D and any observations contributed from b_i will be removed from O^t. This greedy process will be repeated until the most suspicious one is found and is regarded as an unmoved one. Our experience

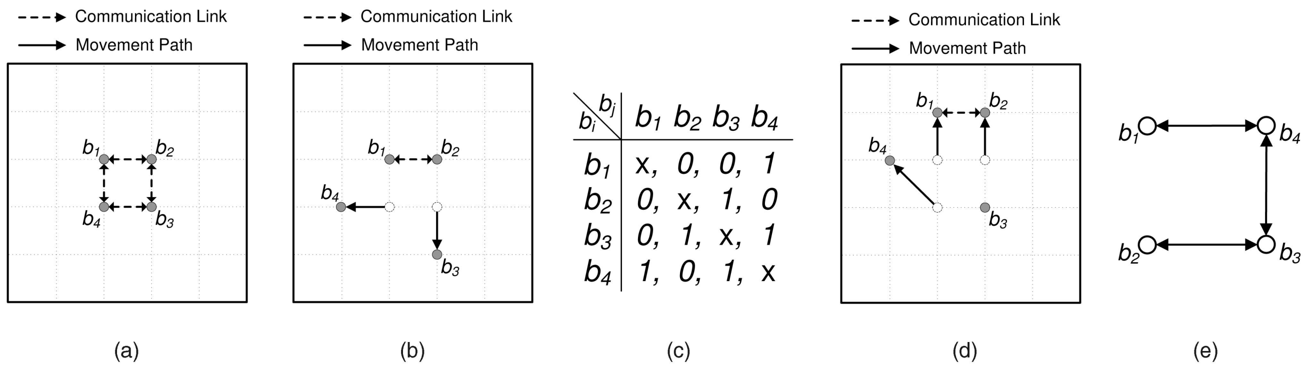

Fig. 4. An example of BMD problem in the NB scheme: (a) the original relation, (b) a movement scenario, (c) observation matrix O^t, (d) another movement scenario, and (e) the observation graph G_O.

shows that this greedy strategy can identify most of the unreliable beacons.

4.2 Neighbor-Based Scheme

In the previous LB scheme, we report the observations according to the received signal strengths directly. It is sensitive to any slight movement. Hence, the NB scheme is designed to hide the information of signal strengths and just report binary observations to the BMD engine. In this scheme, each beacon b_i monitors the change of neighborhood relations with other beacons in its coverage area. The neighborhood relation of b_i at time t is defined as

$$n_{i,j}^t = \begin{cases} 1, & \text{if } b_i \text{ can hear } b_j, \\ 0, & \text{otherwise.} \end{cases}$$

Let $n_{i,j}^0$ be the original neighborhood relation when the system was first configured. Then the observation $o_{i,j}^t$ of b_i on b_j at time t is $o_{i,j}^t = n_{i,j}^t \otimes n_{i,j}^0$, where $\otimes$ is the "exclusive-or" operator. An example with four beacons is shown in Fig. 4a, where the coverage of each beacon is a circle of radius one. Initially, each beacon is in the coverage of two neighboring beacons. Suppose that at time t, beacons b_3 and b_4 are moved as shown in Fig. 4b. If the tolerable regions are defined in such a way that each beacon can only move no more than one grid length, then the observation matrix O^t is as shown in Fig. 4c. Note that due to the asymmetric property of radio propagation, $o_{i,j}^t = 1$ does not imply $o_{j,i}^t = 1$. Hence, the matrix O^t could be asymmetric.

Unfortunately, given an observation matrix O^t, it is possible to come up with other beacon movement scenarios that result in the same O^t. For example, the movement scenario in Fig. 4d also has the same observation matrix as shown in Fig. 4c. In fact, we can prove a stronger result that such ambiguity always exists.

Definition 1. *An observation matrix O^t obtained in the NB scheme is ambiguous if there exist two different movement scenarios B_M and B'_M such that 1) both B_M and B'_M result in the same O^t and 2) $B_M \cap C(O^t) \neq B'_M \cap C(O^t)$, where $C(O^t)$ is the candidate set such that $C(O^t) = \{b_j | O^t[i,j] = 1$ or $O^t[j,i] = 1, 1 \leq i \leq n, 1 \leq j \leq n\}$ and $C(O^t) \neq \emptyset$.*

Condition 2 is to ensure that there is a nontrivial difference between B_M and B'_M. Each beacon in $C(O^t)$ is detected to be moved by at least one other beacon.

Theorem 1. *Given any movement scenario B_M and its corresponding observation matrix O^t obtained in the NB scheme, we can always find another movement scenario B'_M such that O^t is ambiguous.*

Proof. Given any B_M and its corresponding O^t, we can easily compute $B_M \cap C(O^t)$. To construct another B'_M, we first pick any beacon $b_k \in B_M \cap C(O^t)$ and move all beacons in $B_M - \{b_k\}$ to their new locations, as specified in the movement scenario B_M. Let the corresponding observation matrix of yet-to-be-constructed movement scenario B'_M be $\hat{O}^t$. We shall show that $O^t = \hat{O}^t$. For the time being, for any beacons b_i and $b_j \in B$ such that $b_i \neq b_k$ and $b_j \neq b_k$, we can derive that $\hat{O}^t[i,j] = O^t[i,j]$.

Next, suppose that in the movement scenario B_M, beacon b_k is moved from location ℓ_1 to ℓ_2. Let the moving vector $\vec{v} = \ell_2 - \ell_1$. Then, we move all beacons except b_k (i.e., $B - \{b_k\}$) by the vector $-\vec{v}$. Such movements will not change the entries $O^t[i,j]$ and $\hat{O}^t[i,j]$ for all $i \neq k$ and $j \neq k$. Also, these movements will not change the relative locations of b_i and b_k for all $b_i \in B - \{b_k\}$, i.e., $\hat{O}^t[k,i] = O^t[k,i]$ and $\hat{O}^t[i,k] = O^t[i,k]$ for all i. Clearly, the new movement scenario will lead to $\hat{O}^t = O^t$. Furthermore, $b_k \in B_M \cap C(O^t)$ and $b_k \notin B'_M$, which implies that $b_k \notin B'_M \cap C(\hat{O}^t)$, so this theorem is proved. □

An example of the proof of Theorem 1 is shown in Fig. 4d. Let B_M be the movement scenario in Fig. 4b. To construct B'_M, b_3 is kept unchanged and b_4 is moved as scheduled. Then b_1, b_2, and b_4 are moved in the direction $(0,1)$ (the reverse of b_3's moving vector $(0,-1)$). This shows that the matrix O^t in Fig. 4c is ambiguous.

Clearly, the above ambiguity property prohibits us from finding the exact B_M given any O^t. In the NB scheme, our derivation will rely on the assumption that unreliable beacons are only a small proportion among all beacons. This assumption is reasonable because, in practice, beacons are usually moved by accident. Hence, we will try to construct a set B_D that is as small as possible. First, we transform matrix O^t to a directed *observation graph* $G_O = (V, E)$, where $V = C(O^t)$ and $E = \{\langle b_i, b_j \rangle | O^t[i,j] = 1, b_i \in V, b_j \in V\}$. Recall that O^t could be asymmetric, so we define G_O as a directed graph. Second, observe that if $\langle b_i, b_j \rangle$ exists, then not only b_i but also b_j is suspicious. We may consider b_i to be suspicious because the existence of $\langle b_i, b_j \rangle$ may result

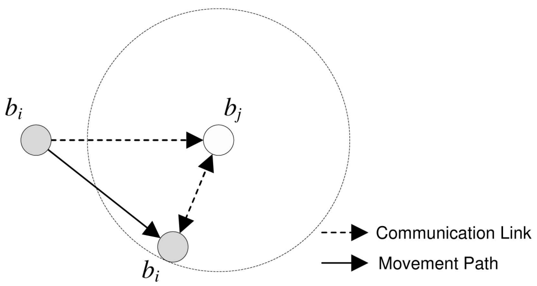

Fig. 5. An example of the appearance of edge $\langle b_i, b_j \rangle$ in G_O caused by the movement of b_i. Note that we assume that the communication range of b_i is larger than that of b_j.

from the movement of b_i and the change of link property between b_i and b_j. For example, in Fig. 5, the link between b_i and b_j is changed from an asymmetric link to a symmetric one (we are assuming a larger coverage for b_i) due to the movement of b_i. Therefore, the problem can be regarded as a *vertex cover* problem [8], whose goal is to find the smallest set $V' \subseteq V$ such that, for each $\langle b_i, b_j \rangle \in E$, $b_i \in V'$ or $b_j \in V'$ or both. For example, Fig. 4e represents the observation graph of the O^t in Fig. 4c.

The minimum vertex cover problem is known to be NP-complete. Hence, after constructing graph G_O, the NB scheme adopts a heuristic approach as follows. If a beacon b_i's in-degree in G_O is higher, it is more suspicious to be moved. So the engine sorts the vertices in G_O according to their in-degrees of the uncovered edges in a descending order, and then selects the first one. This node is included in B_D if any edge incident to it has not been covered. After selecting the most suspicious one, we will sort the vertices again. This process is repeated until a vertex cover is found (all edges in G_O are covered).

4.3 Signal Strength Binary Scheme

In the previous NB scheme, we only consider the neighborhood relations between beacons. The LB scheme is more accurate because it considers the change of locations of beacons. In the SSB scheme, we assume that beacons can measure the signal strengths of HELLO packets from their neighbors. However, beacons do not report these measurements to the BMD engine directly. Instead, each beacon b_i evaluates the amount of signal strength change of each neighboring beacon b_j locally and only reports a *binary* value to the BMD engine. Let the observed signal strength by b_i on b_j at time t be $s^t_{i,j}$ (when $t = 0$, it means the initial observed signal strength). The observation $o^t_{i,j}$ of b_i on b_j is

$$o^t_{i,j} = \begin{cases} 1, & \text{if } s^t_{i,j} \geq \delta^+_{i,j} \text{ or } s^t_{i,j} \leq \delta^-_{i,j}, \\ 0, & \text{otherwise,} \end{cases}$$

where $\delta^+_{i,j}$ and $\delta^-_{i,j}$ are the predefined thresholds of signal strength variations. Note that if beacon b_i does not hear any signals from b_j, we let $s^t_{i,j} = s_{min}$, where s_{min} denotes the minimum signal strength.

The thresholds $\delta^+_{i,j}$ and $\delta^-_{i,j}$ of each pair of beacons b_i and b_j can be determined by the tolerable region R_j of b_j. Within the tolerable region R_j, we pick several sampling points. For example, in Fig. 6, four sampling points p_1, p_2, p_3, and p_4 are collected on the east, west, south, and north sides of the boundary of R_j. For each neighboring beacon b_i, we measure the average signal strength at each of these sampling points, assuming that b_j is moved to this sampling point. Note that if beacon b_i does not hear any signals from b_j at a sampling point, we let its average signal strength be s_{min}. Among all sampling points, the average signal strength at the point with the largest value is selected as the value of $\delta^{max}_{i,j}$ and the one with the smallest value is selected as the value of $\delta^{min}_{i,j}$. Then, considering the effect of noise, we further add a tolerable threshold Δ_{SSB} and set $\delta^+_{i,j} = \delta^{max}_{i,j} + \Delta_{SSB}$ and $\delta^-_{i,j} = \delta^{min}_{i,j} - \Delta_{SSB}$.

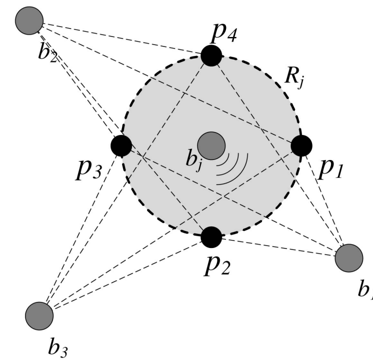

Fig. 6. Determining thresholds $\delta^+_{i,j}$ and $\delta^-_{i,j}$ by the tolerable region R_j of b_j in the SSB scheme.

The major difference between the NB scheme and the SSB scheme is the calculation of local observation. However, the ambiguity property still holds.

Definition 2. *An observation matrix O^t obtained in the SSB scheme is ambiguous if there exist two different movement scenarios B_M and B'_M such that 1) both B_M and B'_M result in the same O^t and 2) $B_M \cap C(O^t) \neq B'_M \cap C(O^t)$, where $C(O^t)$ is the candidate set such that $C(O^t) = \{b_j | O^t[i,j] = 1 \text{ or } O^t[j,i] = 1, 1 \leq i \leq n, 1 \leq j \leq n\}$ and $C(O^t) \neq \emptyset$.*

Theorem 2. *Given any movement scenario B_M and its corresponding observation matrix O^t obtained in the SSB scheme, we can always find another movement scenario B'_M such that O^t is ambiguous.*

Proof. The proof is similar to that of Theorem 1. Given B_M, we can construct another movement scenario B'_M in a similar way. Still, we can prove that 1) for any beacons b_i and $b_j \in B$ such that $i \neq k$ and $j \neq k, \hat{O}^t[i,j] = O^t[i,j]$, and 2) for all $i \neq k$, we can derive that $\hat{O}^t[k,i] = O^t[k,i]$ and $\hat{O}^t[i,k] = O^t[i,k]$. To prove 1), we move all beacons in $B_M - \{b_k\}$ to their new locations as specified in the original movement scenario. To prove 2), we move all beacons except b_k by an opposite moving vector of the original moving vector of b_k. After these movements, the relative positions of beacons are the same as that in the movement scenario B_M. Hence, $s^t_{i,j}$ equals the new observed signal strength ${s^t_{i,j}}'$ in B'_M. Besides, the threshold $\delta^+_{i,j}$ and $\delta^-_{i,j}$ for each pairs b_i and b_j only depend on b_j's tolerable region and the initial deployment, so these observation matrices will be identical. □

Based on changes of signal strengths, the BMD engine for the SSB scheme can work similarly to that for the NB scheme, except that the observations are computed by each beacon by a different criteria. So we omit the details. However, with more accurate information, this scheme is expected to perform better than the NB scheme. We will verify this through simulations in Section 5.

4.4 Signal Strength Real Scheme

Similarly to the previous SSB scheme, the SSR scheme assumes that beacons can measure the signal strengths from their neighboring beacons. However, in this scheme, the *real* signal strength variations, instead of binary values, observed by a beacon are reported to the BMD engine. Specifically, the observation $o^t_{i,j}$ is

$$o^t_{i,j} = \left|s^t_{i,j} - s^0_{i,j}\right|.$$

Similarly to the previous schemes, the ambiguity property still remains.

Definition 3. *An observation matrix O^t obtained in the SSR scheme is ambiguous if there exist two different movement scenarios B_M and B'_M such that both B_M and B'_M result in the same O^t.*

Theorem 3. *Given any movement scenario B_M and its corresponding observation matrix O^t obtained in the SSR scheme, we can always find another movement scenario B'_M such that O^t is ambiguous.*

Proof. The proof is similar to that of Theorem 2. The same approach is applied to construct another movement scenario B'_M. We can observe that B'_M is a shifted movement scenario of B_M. This means that the relative distance of any beacon b_i to its neighbor b_j in B_M is the same as the relative distance of the corresponding beacon b'_i and b'_j in B'_M. Hence, $O^t[i,j] = \hat{O}^t[i,j]$ for all i and j. □

To avoid the effect of slight signal fluctuation and tolerable movement, we apply the following two rules to filter out those small values in the observation matrix: In the first rule, we remove the observations affected by small noises. We define a new $n \times n$ matrix X such that

$$X[i,j] = \begin{cases} 0, & O^t[i,j] < \Delta_{SSR}, \\ O^t[i,j], & \text{otherwise}, \end{cases}$$

where Δ_{SSR} is a tunable threshold value. Hence, we drop the observations that are insignificant. In the second rule, we intend to avoid selecting those beacons whose movements are within their tolerable regions. We filter out all observations on b_j if the summations of signal strength changes observed by other beacons are below a threshold η_i. So, we define another $n \times n$ matrix X' such that

$$X'[i,j] = \begin{cases} 0, & \sum_{k=1}^{n} O[k,j] < \eta_j, \\ X[i,j], & \text{otherwise}, \end{cases}$$

where η_j is related to the tolerable region R_j of b_j. To determine a suitable η_j, we adopt a similar sampling strategy as shown in the SSB scheme. The threshold η_j of beacon b_j is calculated by an approximation as follows. Within the tolerable region R_j, we pick several sampling points. For example, four sampling points are selected on the east, west, south, and north sides of the boundary of R_j in Fig. 6. For each sampling point, we measure the sum of signal strength changes observed by other beacons assuming that b_j is moved to that sampling point. The sum of the signal strength changes at the point with the smallest value which is selected as the value of η_j.

Next, we convert the problem to the *minimum weight vertex cover problem* [10]. We define a directed weighted observation graph $G_O = (V, E)$, where $V = \{b_j | \sum_{i=1}^{n} X'[i,j] \neq 0\}$ and $E = \{\langle b_i, b_j\rangle | X'[i,j] \neq 0, b_i \in V, b_j \in V\}$. Similar to the NB and SSB schemes, we suspect that b_i or b_j has been moved if $\langle b_i, b_j\rangle$ exists. The *suspicion degree* of beacon b_i is defined as $w_s(b_i) = \sum_{j=1}^{n} X'[j,i]$. The maximum suspicion degree is written as $w^*_s = \max_{i=1..n}\{w_s(b_i)\}$. A weight function $w : V \mapsto R^+$ is then defined for each $b_i \in V$ such that $w(b_i) = w^*_s - w_s(b_i)$. According to the definition of the minimum weight vertex cover problem, we try to find a vertex cover $V' \subseteq V$ such that if $\langle b_i, b_j\rangle \in E$, then $b_i \in V'$ or $b_j \in V'$ or both, and the sum $\sum_{b_i \in V'} w(b_i)$ is minimized. Note that the minimum weight vertex cover problem is still NP-complete.

From the above formulation, we have converted our BMD problem to the minimum weight vertex cover problem. Then, the SSR scheme adopts a heuristic strategy to find a vertex cover with the minimum weight in G_O. For each beacon b_i, we define a cost metric $c_i = w(b_i)/UE(b_i)$, where $UE(b_i)$ is the number of uncovered edges of b_i. Then, the beacon with the minimum cost metric is included in our solution. Then we compute the cost metrics of those beacons that are affected due to the selection of the above beacon and pick the next beacon with the minimum cost metric. This is repeated until all edges are covered.

5 Simulation Results

In this section, we present our simulation results to evaluate the proposed schemes. Ideally, we would expect that $B_M = B_D$. However, for many practical reasons, this may not be achieved. For ease of discussion, we define two events. A *hit event* occurs for a beacon b_i if $b_i \in B_M$ and the BMD engine also determines that $b_i \in B_D$. A *false event* occurs for b_i if $b_i \notin B_M$ but $b_i \in B_D$. We also use the results to calibrate the positioning engine and measure the localization error when there are unnoticed beacon movement events (i.e., we compare the positioning accuracy when our schemes are applied against the fact that no action is taken with the existence of beacon movement events). Experiments are conducted under different conditions, such as the ratio of moved beacons, the maximum movement distance, the degree of radio irregularity, the degree of varied sending power, and the noise level of the environment. Also, we adopt a close-to-reality radio model called RIM [28] to conduct our simulations.

5.1 Simulation Model

The sensing field is a $300\ \mathrm{m} \times 300\ \mathrm{m}$ area. There are 20 beacons randomly deployed on this field with the restriction that the distance between any two beacons is at least 5 m. This restriction is to avoid some beacons being placed too crowded, thus reducing the detection capability of the network. When a scenario violating the restriction is generated, we will discard it and regenerate another one.

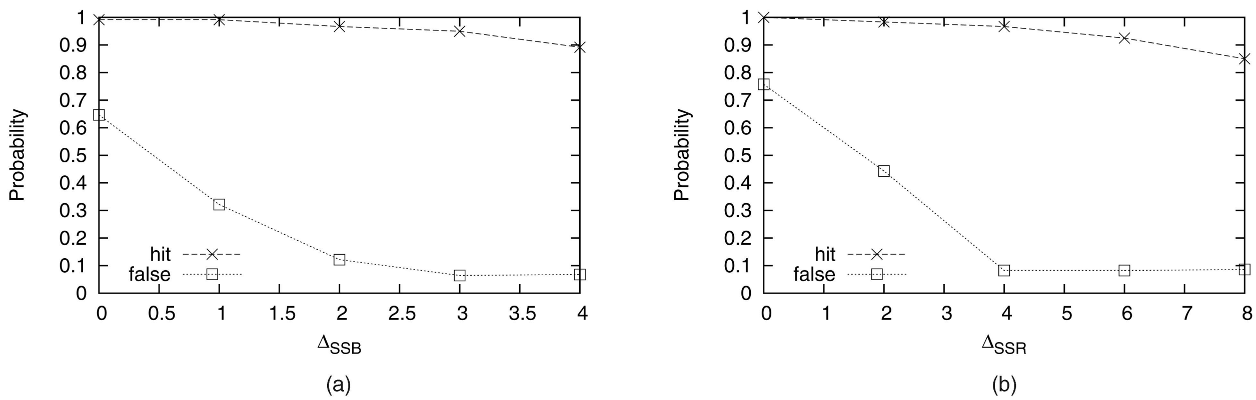

Fig. 7. Evaluation of hit and false probabilities for (a) the SSB scheme under different Δ_{SSB} and (b) the SSR scheme under different Δ_{SSR}.

Moved beacons are chosen randomly and a parameter *moved ratio* (MR) is used to control the number of moved beacons. The moving distance is uniformly distributed between $MD - 50$ and MD, where MD is a parameter called *moved degree*. The tolerable region of the movement of each beacon is a circle centered at the beacon with a radius of 20 m. Note that constrained by the tolerable regions, only part of the moved beacons will be considered moved.

Based on RIM [28], the received signal strengths at a distance of d is modeled by

$$P_r(d) = P_t^{VSP} - PL^{DOI}(d) + N(0, \sigma_f), \quad (1)$$

where P_t^{VSP} is the transmit power, which may vary among different hardware, $PL^{DOI}(d)$ is the path loss, which has a nonisotropic and continuous property, and $N(0, \sigma_f)$ is a zero-mean normal random variable with a standard deviation σ_f to stand for dynamically shadowing noise.

RIM introduces the *variance of sending power (VSP)* to model the impacts of hardware difference and remaining battery of a device on transmit power

$$P_t^{VSP} = P_t \times (1 + N(0, \mathtt{VSP})), \quad (2)$$

where P_t denotes the initial transmit power and $N(0, \mathtt{VSP})$ is a zero-mean normal random variable with a standard deviation VSP. The parameter VSP controls the degree of variance of sending power among different beacons. Each beacon randomly selects its P_t^{VSP} when the simulation starts.

In real-world experiments, the irregularity of signal fading is a common phenomenon. However, most path loss models do not take this nonisotropic property of signal coverage into consideration. To capture this effect, RIM imports a *degree of irregularity (DOI)* to control the amount of path loss in different directions, i.e.,

$$PL^{DOI}(d) = PL(d) \times K_i, \quad (3)$$

where $PL(d)$ is the optimal obstacle-free path loss formulation

$$PL(d) = PL(d_0) + 10\phi log\frac{d}{d_0}, \quad (4)$$

where d_0 is the reference distance (here we set $d_0 = 1$). The coefficient K_i is to model the level of irregularity at degree i ($i = 0..359$) such that

$$K_i = \begin{cases} 1, & \text{if } i = 0, \\ K_{i-1} \pm W(0, \sigma_d, \gamma) \times \mathtt{DOI}, & \text{if } i = 1..359, \end{cases} \quad (5)$$

where $|K_0 - K_{359}| \leq \mathtt{DOI}$ and $W(0, \sigma_d, \gamma)$ is a zero-mean Weibull random variable. The parameter DOI controls the allowable difference of two successive degrees. When $K_i = 1$, it implies an ideal path loss model. When K_i deviates more from 1, it means a greater deviation from the ideal path loss formulation. Note that (5) is a discrete model with 360 discrete values. To extend to a continuous model, one may adopt an interpolation mechanism.

All results are from the average of 20 experiments. To reduce the influence of noise, signal strength is calculated from the average of 50 HELLO packets. The default simulation parameters are set to $P_t = 15$ dBm, $d_0 = 1$ m, $PL(d_0) = 41.5$ dBm, $\phi = 3.3$, $\sigma_f = 2$, $\mathtt{VSP} = 0.2$, $\mathtt{DOI} = 0.005$, $\sigma_d = 0.1$, and $\gamma = 1$.

5.2 Parameters of the SSB and SSR Schemes

Before conducting thorough simulation studies, we first tune the parameters of the SSB and SSR schemes. In these schemes, we have two thresholds Δ_{SSB} and Δ_{SSR} to eliminate the effect of signal fluctuation and irregularity, respectively. Generally speaking, larger thresholds incur higher hit probabilities and lower false probabilities. Fig. 7 illustrates the hit and false probabilities of SSB and SSR under different values of thresholds. Hence, based on these results, we let $\Delta_{SSB} = 3$ and $\Delta_{SSR} = 6$.

5.3 Probabilities of Hit and False Events

In this simulation study, we evaluate the hit and false probabilities of the proposed schemes under different environmental conditions. Here, we define the hit probability as the frequency of occurrence of hit events, e.g., $\frac{|B_D \cap B_M|}{|B_M|}$, and the false probability as the frequency of occurrence of false events, e.g., $\frac{|B_D - B_M|}{|B - B_M|}$. First, in Fig. 8a, we vary the noise level by adjusting the standard deviation σ_f of RIM from 0 and 4. As expected, the NB scheme performs the worst because it is too insensitive to beacon movement events. Hence, only a few beacon movement events are correctly detected and many unmoved beacons are falsely alarmed. Under our simulation parameters, the LB scheme can detect all beacon movement events under different noise levels, but it has higher false probability than SSB and SSR.

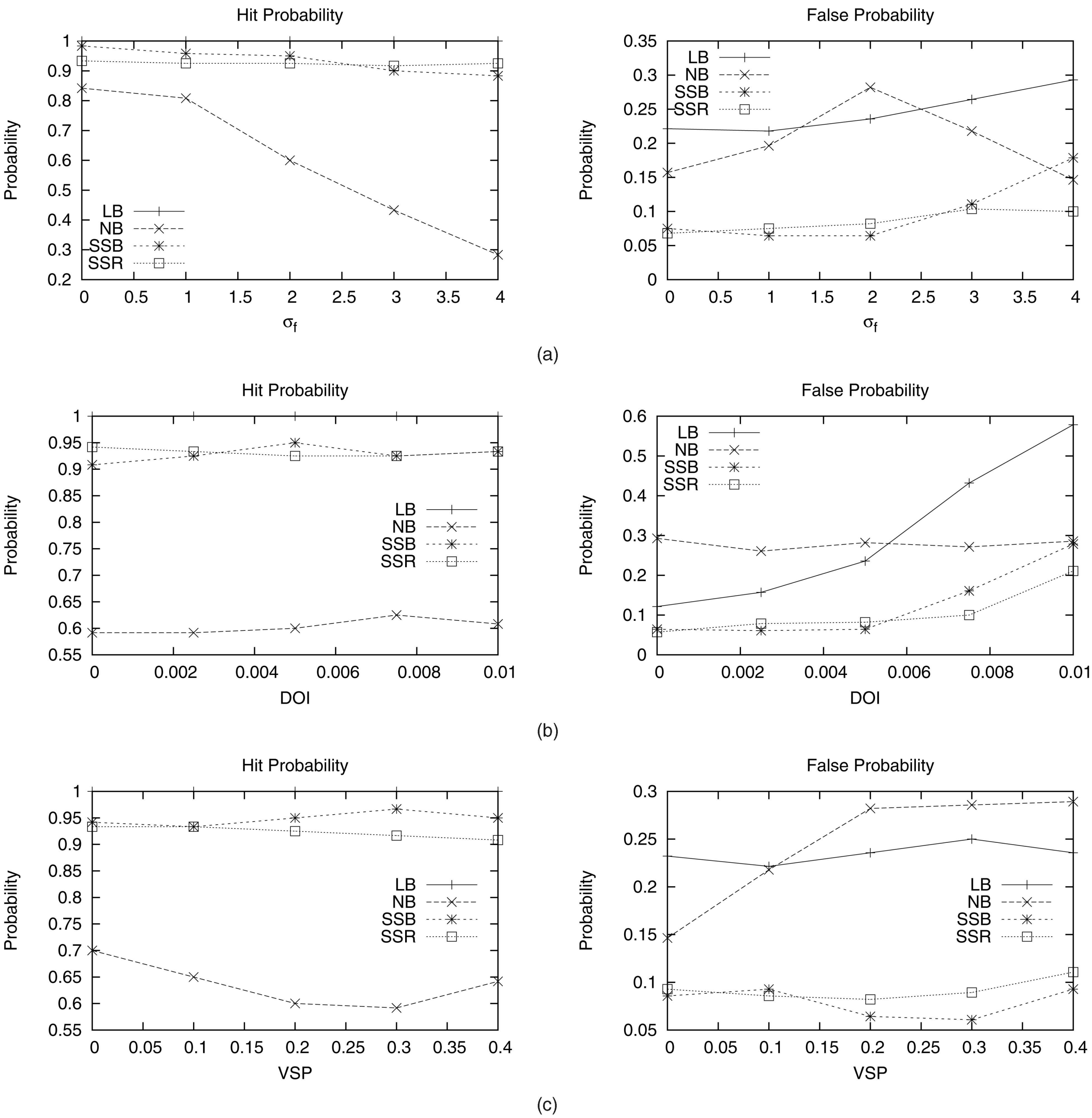

Fig. 8. Comparison of hit and false probabilities by varying (a) the standard deviation σ_f, (b) the degree of irregularity `DOI`, and (c) the varied sending power `VSP` of the RIM radio model.

In Fig. 8b, we study the influence of the radio irregularity on each scheme. We can observe that the false probabilities of SSB, SSR, and LB increase as the radio propagation is more irregular. For SSB and SSR, their false probabilities are high due to their static thresholds Δ_{SSB} and Δ_{SSR}, which prohibit them from dynamically adjusting themselves to fit to the environment. For LB, it initially outperforms NB when the degree of irregularity is low, but is outperformed by NB as the degree of irregularity becomes higher than 0.006.

Fig. 8c illustrates the influence of beacons' variable sending power. Larger values of `VSP` mean that beacons' sending power is of higher degree of differences, which in turn imply that we may see more asymmetric links between beacons. Since our modeling has considered asymmetric links, all schemes except the NB scheme can handle such situations well. For the NB scheme, we see a significant increase in its false probability.

5.4 Movement Degrees and Movement Ratios

In Fig. 9a, we vary the values of MR between 0.1 and 0.5 to make the comparison. In terms of the hit probability, the LB scheme performs the best, followed by SSB, SSR, and then NB. However, the LB scheme also induces the highest false probability. As a result, SSB and SSR are considered the best, which provide a hit probability over 0.85 and a false probability under 0.17 even when the MR is 0.4. The NB scheme always has the worst hit and false probabilities due

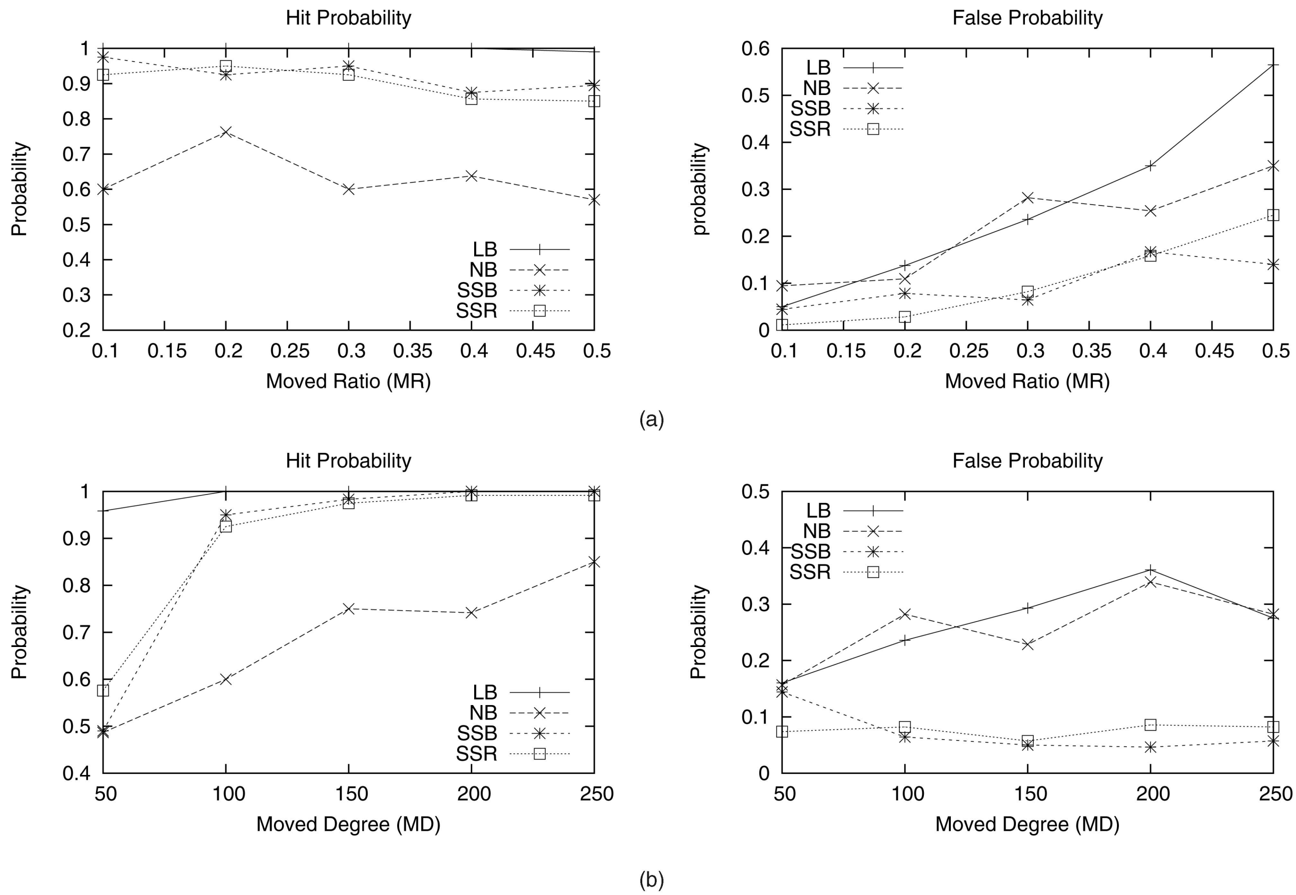

Fig. 9. Comparison of hit and false probabilities by varying (a) the MR value and (b) the MD value using the RIM radio model.

to its oversimplified detection model. The high false probability of the LB scheme can be explained by its high sensitivity to signal change. Since beacons will all report their observations, the movement of a beacon can easily propagate errors to its neighboring beacons. Thus, a lot of reliable beacons will be reported as unreliable. The same phenomenon can also be seen for the SSR scheme when the MR gets higher. However, its false probability is much less than that of the LB scheme.

In Fig. 9b, we vary the MD. Generally, because a larger MD means that each movement is more dramatic, this is beneficial for our detection work. Therefore, we see increases of hit probabilities and decreases of false probabilities as MD increases in all schemes except the NB and LB schemes. Again, this demonstrates that the NB scheme is oversimplified and the LB scheme is too sensitive.

Furthermore, we are interested in the evaluation of MD and MR under the ideal log-distance path loss model. Recall that when $VSP = 0$ and $DOI = 0$, RIM actually reduces to the log-distance model. The results are shown in Fig. 10. Comparing Figs. 9 and 10, we can observe that they have similar trends. Beside, both the hit and false probabilities are improved under the log-distance model, because its radio propagation is more predictable.

5.5 Effect of Beacons' Density

Intuitively, more beacons are beneficial to the BMD problem. More beacons imply that each beacon has a chance to be monitored by more neighboring beacons, so the hit and false probabilities may be improved. We can verify this claim in Fig. 11. As the number of beacons increases, the hit probabilities of all schemes are improved. As for the false probability, only minor improvement can be seen for the SSB and SSR schemes. However, we see noticeable improvement for LB. When the number of beacons is more than 25, the false probability of LB will be comparable with SSB and SSR. The reason is that the positioning accuracy also improves as the number of beacons increases. This proves that the performance of LB is highly dependent on the positioning accuracy. Hence, we can conclude that in a denser scenario with many beacons, the LB scheme is an ideal choice because it gives a comparable hit probability and a lower false probability. However, in a sparser environment, the SSB and SSR schemes are better choices because of not only their performance but also their lower complexity.

5.6 Impact of BMD on Localization Accuracy

After determining the moved set B_D, the positioning engine should be recalibrated to improve its positioning capability. We adopt the pattern-matching localization algorithm [3] in our simulation, where the location database contains the signal vector $\boldsymbol{v}_i = [v_{i,1}, v_{i,2}, \ldots, v_{i,n}]$ of each training location ℓ_i in the sensing field, where $v_{i,j}$ is the average signal strength of beacon b_j observed at location $\ell_i, i = 1..m$. For the calibration purpose, we will ignore the element $v_{i,j}$

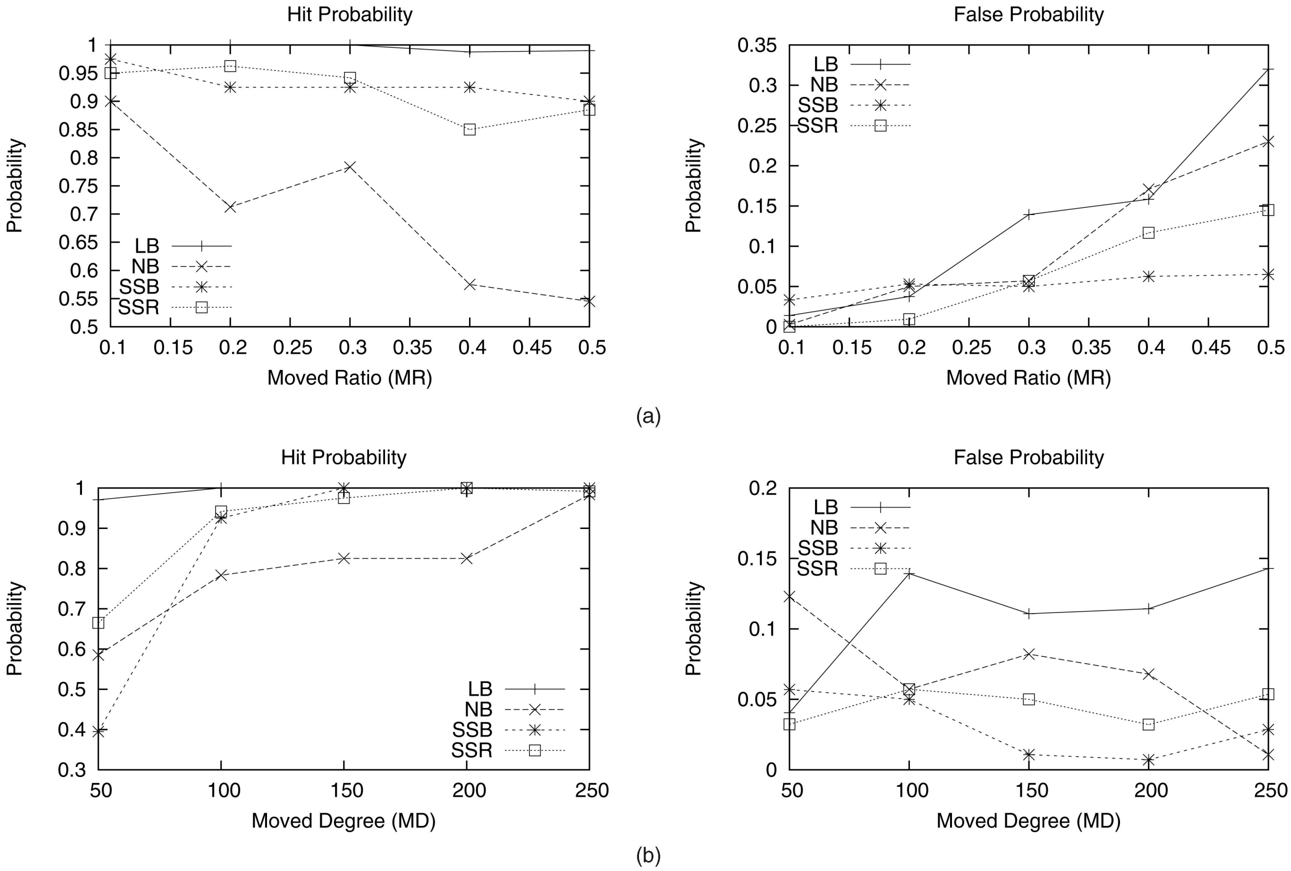

Fig. 10. Comparison of hit and false probabilities by varying (a) the MR value and (b) the MD value using the log-distance radio model.

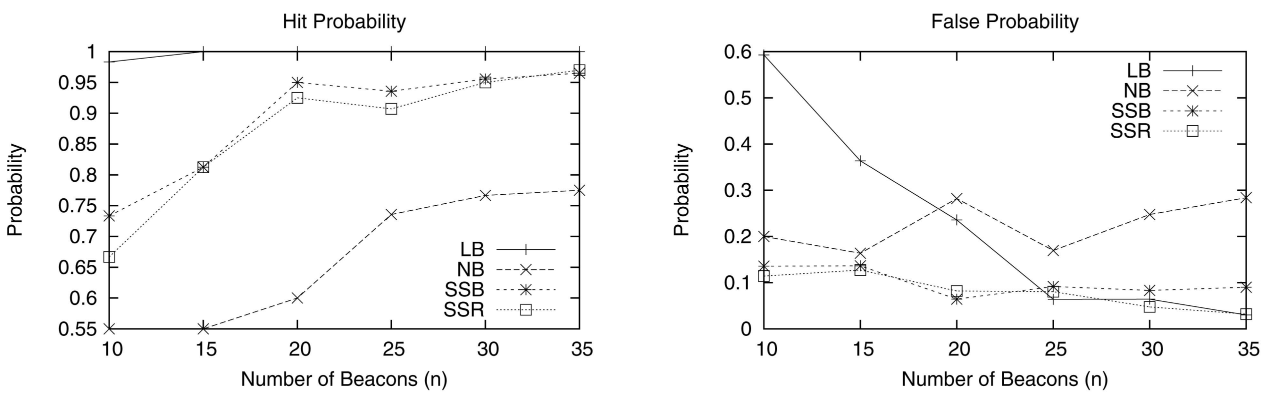

Fig. 11. Comparison of hit and false probabilities by varying the density of beacons.

corresponding to each $b_j \in B_D$ during the localization procedure. Clearly, this will reduce the number of beacons to be referenced (including hit and false ones). However, if contributions from those moved beacons are not deleted, the errors may be high. In the following, we will evaluate how our schemes can improve localization errors if there exist beacon movement events.

In our experiment, we collect 961 training locations at locations $(10 \times i, 10 \times j)$, for $i = 0..30$ and $j = 0..30$. Then, in the positioning phase, we simulate a moving object in the field following the random waypoint model. It will switch between a moving state and a pausing state. In the moving state, it will randomly select a destination in the sensing field and move to it at a constant speed of 1 m/sec. After reaching the destination, it will switch to the pausing state and stay there for 3 seconds. The tracked object also measures the signal strengths of all beacons every 1 second. The total simulation time is 1,000 seconds. We compare our results against the *Optimal* case, where the hit probability is always 1 and the false probability is always 0, and the *no_BMD* case, where the hit probability is always 0 and the false probability is always 0 (i.e., no special action is taken).

Figs. 12a and 12b illustrate the average positioning errors under different MR and MD, respectively. The results in Fig. 12a demonstrate that SSB and SSR incur positioning errors closest to the *Optimal* case. One interesting simulation result is that NB's errors are quite unacceptable, sometimes even worse than the *no_BMD*

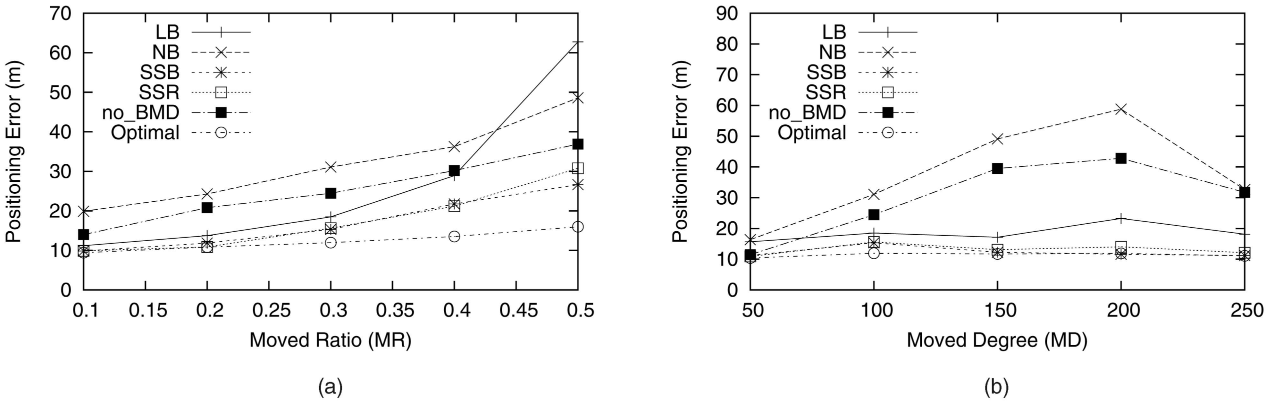

Fig. 12. Comparison of average localization errors by varying (a) the MR value and (b) the MD value.

case. This is because of its low hit probability and high false probability. LB is slightly worse than SSR when $MR \leq 0.3$. However, referring to Fig. 9a, we see that LB also has high false probabilities as MR increases. Hence, when $MR = 0.5$, LB's positioning errors are higher than those of the other schemes.

The comparisons of the positioning errors under different values of MD are shown in Fig. 12b. The trends are similar. Under all simulated MR, SSB and SSR perform very close to the *Optimal* case. NB incurs the worst performance.

To model the error recovery capability using the *Optimal* case as the baseline, we propose the following Error Improvement Ratio metric:

$$EIR(BMD\_Scheme) = \frac{\mathrm{error}_{no\_BMD} - \mathrm{error}_{BMD\_Scheme}}{\mathrm{error}_{no\_BMD} - \mathrm{error}_{Optimal}} \times 100\%.$$

The ideal value of EIR is 100 percent. However, this is hard to achieve because our current results cannot achieve 100 percent hit and 0 percent false probabilities. For example, under the default settings, the EIR values are 47.77, -58.85, 72.99, and 70.66 percent for LB, NB, SSB, and SSR, respectively.

6 Conclusions

In this paper, we have identified a new BMD problem in wireless sensor networks for localization applications. This problem describes a situation where some beacon sensors which participate in the localization procedure are moved unexpectedly, called beacon movement events. The negative impact is a reduced localization accuracy if we disregard such events. We propose to allow beacons to monitor each other to identify such events. Four schemes are presented for the BMD problem. Moreover, we have proven some ambiguity theorems which may prohibit the BMD problem from being solved correctly under some situations. Some heuristics are proposed by mapping the BMD problem to the vertex-cover problem. Hit and false probabilities of these heuristics are obtained through simulations under a realistic radio irregularity model [28]. It is shown that the best heuristics, SSB and SSR, have an error improvement ratio of more than 70 percent in most cases. As to future work, it deserves to further investigate the BMD problem if there is some trust model among beacons. Based on the observations contributed from the trust model, the BMD problem should be solved more effectively. Besides, in this paper, we omit the observations from the moved beacons to avoid more serious positioning errors in the localization process. It could be more beneficial to the localization system if we can relocate those moved beacons. Finally, a variant of the beacon movement detection problem, when there are some mobile beacons which may move away from their original moving trajectories, also deserves further investigation.

Acknowledgments

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